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Revised Final Report

Task 4: Analysis of Food Stamp
Participation Time Series
Net Flows Model

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Analysis of Food Stamp Participation Time Series
(The Net Flows Model)

ABSTRACT

We construct and estimate a model of the monthly change in the state food stamp caseload of individuals. Our data are pooled cross-sectional and time series observations; state-specific program information is combined with exogenous data on economic and demographic characteristics and pooled over the time period from 1970 to 1983. In principal, the change in the food stamp caseload at any time t is a function of economic conditions, demographic characteristics of the population, and program parameters and procedures, including those of programs related to food stamps.

We estimated the model over the period from 1970-1983 and separately from 1976-1983 to focus on more recent program changes. The results of our estimation over the later period highlight the role played by several key factors. First, the population and its distribution by age are important determinants. In general, the greater the number of very young children, the higher the net flow of food stamp cases. The opposite is true for persons over 65, however. Second, changes in economic conditions affect the net flows in a complex fashion, largely through the impact of changing unemployment conditions and their interaction with the business cycle. In general, as the unemployment rate rises, there is an increase in the net flow of food stamp cases. However, this increase is muted (1) the lower the initial level of unemployment, (2) the higher the insured unemployment rate, or (3) if a peak in the business cycle occurs. In addition, if unemployment rates are rising through time, there is an even greater tendency for the net flow to rise in the face of a fixed percentage increase in unemployment rates.

Third, certain program parameters are indeed important determinants of food stamp case openings and closings. AFDC case openings and closings are highly related, and in the expected direction. Program benefits received, with the possible exception of food stamp benefits, are not significantly related. Our results underline the tremendous importance of the elimination of the purchase requirement, but we are not able to support the hypotheses that implementation of 1981 OBRA and 1982 OBRA legislation had any impact on changes in the food stamp caseload. Finally, there appears to be an additional fixed effect, not related to economic, demographic, or legislated program changes that has had a depressing influence on the net flow of cases in years since 1980.

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I. Introduction

In 1981 and 1982 legislation was enacted which directly affected the administration and benefits of the Food Stamp Program (FSP). At the time of enactment there was considerable interest in understanding the full effects of these changes on recipient benefits and caseload growth. However, coincidental to the implementation of certain legislated changes were important economic events--the business cycle peaked in July, 1981 and unemployment rates were rising rapidly throughout 1981 and 1982--which complicated the task of disentangling legislative effects on program variables from the economic effects.

In this report we present estimates of the effects on food stamp caseload flows of program changes legislated in 1981 and 1982. Estimates of these effects were obtained from an analysis of state-level food stamp time series data which specifically controlled for differences in economic and demographic characteristics across the states as well as through time. Thus, to the extent possible we isolated the effect of a legislated program change on food stamp caseloads from the effects of changing economic and demographic conditions which were occurring simultaneously. Our results show that the legislative impact on caseloads during 1982 and 1983 was very small compared to th economic effects, but, that there has been a persistent tendency since 1980 for caseloads to decline that is not explained by economic or legislative events.

The model that we have used to obtain estimates of the impact of legislated changes is referred to as the "net flows model" where the net flow is defined as the change in the number of food stamp cases from

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month-to-month and is a function of economic conditions, demographic characteristics of the population, and program parameters. Hence, the net flows model contrasts with a stock model in that the latter attempts to predict caseload levels, while the net flows model is focused on the factors which effect the change in the caseload at any point in time.

In particular, the net flows model is characterized by a dynamic perspective on the Food Stamp Program. The change in the caseload at any time is the net of case openings and case closings, and the model therefore includes explanatory variables related to the movement onto and off of the program. Additionally, the model employs variables which affect the pool of eligible participants in the current period as well as in previous periods to account for lagged effects. For example, the number of case openings may be a consequence of current AFDC case openings, demographic factors, seasonal factors, and program rules. In addition, current and lagged economic conditions are expected to be important determinants. The Food Stamp caseload is known to be sensitive to the business cycle, and to employment characteristics in particular. High levels of current unemployment are expected to affect case openings with a lag as people exhaust unemployment insurance coverage and personal savings. Hence, it is important to control for contemporaneous as well as lagged economic conditions.

Of major interest in the analysis of the net flows model is the impact of various program policy changes, particularly changes under 1981 and 1982 OBRA legislation. States implemented the various policy changes at different times. Given enough variation in implementation dates, the marginal impact of a policy change on the net flow of cases, holding constant economic and demographic conditions, can be estimated

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with more confidence. Thus, while the effects of economic and demographic changes are of interest in their own right, primary interest is in estimating the effects of policy changes. Because the net flows model uses micro-data--observations on state-specific variables--the variation in circumstances from state-to-state is great enough to allow the effects of program changes to be isolated.

In the next section we present the conceptual framework on which the empirical model is based. A description of the data set and the variables used in our analysis follows in Section III. In Section IV we present the main findings from a preliminary analysis using OLS. In Section V the model development is described in more detail, including the final form of the model in which the error structure is hypothesized to follow from an error components model--a form often assumed when pooled cross-sectional and time series data are used. A discussion of the policy implications of the model concludes the report in Section VI. Appendix A provides a more detailed description of the variables used; Appendix B is a set of descriptive statistics for the variables used in the net flows analysis.

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II. Conceptual Framework

The purpose of the net flows model is to provide a framework for estimating the effects of certain policy changes upon the change in the food stamp caseload, while simultaneously controlling for other factors, such as the demographic composition of the population, economic conditions, and changes in other relevant programs, such as AFDC. We begin by formulating a model in terms of the components of caseload turnover, that is, case openings and case closings. These variables more closely correspond to the processes underlying the dynamics of the food stamp program. We build into the model a series of relationships between case openings and closings and the exogenous factors which presumably affect program participation. For expository purposes it is useful to make explicit the role of the size of the pool of nonparticipating eligibles, which mediates between exogenous variables and case openings. Both stock and flow variables are relevant to the conceptual model. As an aid to distinguishing these two types, variables corresponding to stocks will be designated with upper-case symbols and flow variables with lower-case symbols.

We begin by defining the variables o_t and c_t, which represent the number of food stamp cases opened, and closed, respectively, during the interval between t-1 and t. Case openings during the interval are drawn from the hypothetical pool of eligible nonparticipants at time t, denoted E_t. The relationship between case openings and the pool of eligibles can be written simply as

$$o_t = r\ E_t, \tag{1}$$

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where r is a type of "participation rate", namely the probability that an individual (household), selected at random from the pool of eligible nonparticipants, has become an active food stamp recipient since the last time period.

However, note that the pool of eligibles, a stock, can be factored into stock and flow components. Thus, we can write

$$E_t = E_{t-1} + ne_t - nie_t \qquad (2)$$

where ne_t equals the number of newly eligible units and nie_t equals the number of previously eligible units who are no longer eligible due to changed circumstances. By recursively substituting into (2), and assuming that there is a finite upper-bound number of time periods that a unit will remain eligible without becoming an active recipient, we obtain

$$E_t = ne_t + ne_{t-1} + \ldots + ne_{t-k} - nie_t - nie_{t-1} - \ldots - nie_{t-k}. \qquad (3)$$

We must now consider the determinants of the flow of households into and out of the pool of food stamp eligibles. Additions to the pool of eligibles can be a consequence of AFDC case openings; changing economic conditions such as layoffs, new entries to the labor force, or strikes; demographic events affecting population composition such as births and deaths, marriages and divorces, and migration; seasonal factors such as agricultural cycles and the school years; and changes in policy variables. The same set of exogenous factors could be assumed to influence withdrawals of households from the pool of eligibles, except that AFDC case closings might also be relevant. Denote

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the full set of exogenous determinants of ne_t and nie_t as x_t. Then, by substitution of (3) and (2) into (1), we have

$$o_t = f(x_t, x_{t-1}, \ldots, x_{t-k}), \tag{4}$$

illustrating the conceptual relevance of a series of lagged exogenous variables to the determination of current-period case openings.

Turning to the other component of net caseload flows, case closings, we would hypothesize that the number of case closings during the interval is determined by caseload characteristics at t-1, and by changing economic conditions and policy changes between t-1 and t -- many of the same factors which determine case openings. Thus,

$$c_t = g(x_t, x_{t-1}, \ldots, x_{t-k}) \tag{5}$$

At any time t, the total size of the food stamp caseload, L_t, equals the size of the load in the previous period plus openings and minus closings.

$$L_t = L_{t-1} + o_t - c_t \tag{6}$$

The net flow can be expressed as,

$$l_t = L_t - L_{t-1} = o_t - c_t \tag{7}$$

combining expressions (4) and (5),

$$l_t = h(x_t, x_{t-1}, \ldots, x_{t-k}). \tag{8}$$

Equation (8) represents a reduced-form relationship among observable variables. It is not necessary to observe several of the key underlying variables, such as E_t -- the pool of eligibles, but it is also true that the parameters of the underlying relationships cannot be identified on the basis of the parameters of (88). Nevertheless, it is useful to formulate the underlying conceptual model in order to develop a framework for interpreting the estimated parameters of the reduced-form equation.

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An estimable form of equation (8) can be obtained by specifying the set of variables which comprise the x vector, assuming a functional form for the relationship between the dependent and independent variables, and adding a stochastic error term. In principle, the stochastic form of equation (8) could be estimated using time-series data for a single jurisdiction. However, multiple program changes may coincide with other period-specific economic events, occurrences which limit our ability to estimate separate impacts. More powerful results can be obtained by assuming that most (or all) of the reduced-form parameters are uniform across jurisdictions (e.g., states) and pooling the time-series data of multiple jurisdictions. In particular, when food stamp program changes are implemented during different time periods in different states, a pooled-sample approach to estimation can capitalize upon the independent variation in program changes and other contemporaneous variables, yielding more precise estimates of the parameters representing program impacts.

If we assume an additive relationship between l_t and x, equation (8), including the stochastic disturbance, becomes

$$l_t = a_o + b_1x_t + b_2x_{t-1} + \cdots + b_kx_{t-k} + \xi_t . \qquad (9)$$

Our assumptions regarding the error structure are highly dependent on the pooled nature of our data and we explicitly address this issue in a later section. For the purpose of preliminary analysis, we impose the assumption that $\xi_t \sim N(0, \sigma^2)$ i.e., the error term is distributed normally through time with constant mean and variance, and employ OLS regression techniques to

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estimate the unknown parameters. Finally, the x vector is comprised of a set of variables which can be broadly classified as geographic, demographic, economic, and program determinants of the net flows.

III. Data Base and Descriptive Analysis

Net Flows Data Base

The core data used in this analysis are monthly reports by each state on the number of food stamp recipients from the publication "Food Stamp Program: Statistical Summary of Operations."[1] Our data consist of reports from July, 1969 through April, 1984. Hence, the data are pooled cross-section and time series observations; for a given month there are 51 state observations (including the District of Columbia).[2]

Appended to the basic food stamp data are measures of economic conditions and demographic characteristics. When possible we have attempted to collect monthly, state-specific variables, but quite often variables of interest are available only quarterly or annually. For example, the distribution of state population by age is available only on an annual basis, as are certain economic variables, such as per capita personal income. While unfortunate, we do not regard the lack of monthly or quarterly data as a major problem. These variables change relatively slowly across time. Measurement on an annual basis will still take into account long term trends in the variables; we make the implicit assumption that the annual measure is a reasonable approximation to the actual value of the variable at any point in the year. In addition, a few variables of interest are not available by state; income distribution is

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1. Starting in July, 1982 the data are published only once per quarter, however, we were able to obtain a complete set of monthly data from FNS staff.

2. In the early years of the program not all states participated so there may not be 51 observations for every month. By 1974 all states had food stamp offices in operation.

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available only for the four census regions and we make use of regional price indexes.

Due to the large number of observations involved and the highly variable nature of the dependent variable, we conduct most of our analysis on quarterly averages. That is, the dependent variable is the average monthly change in the number of participants for a given calendar quarter.[1]

Appendix Table A.1 summarizes the collection of variables included in the data base. Information on sources, the time period covered, and special comments relevant to the data collection are presented for each variable. The independent variables listed in Table A.1 are grouped according to the major categories of geographic, demographic, economic, and program variables. Appendix Tables B.1-B.4 display descriptive statistics for the two periods over which most of our analysis was conducted -- 1970-1983 and 1976-1983. These time periods were chosen for the following reasons. First, although we had data from the second half of 1969, it was "used up" when we created the monthly change in caseloads and the lagged economic variables. In any case, it seemed sensible to begin with 1970:Q1 and end with 1983:Q4. The little data we had for 1984 on food stamp participation could not be used in regression analysis because we had no comparable economic and demographic data. Most of our preliminary analysis was done on data from the full time

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1. Before arriving at this conclusion we did conduct preliminary regression analysis using monthly data on the net flows. The coefficients were relatively robust with respect to the time measurement of the unit of analysis, however, we were able to explain substantially less of the total variance in the regression. Because the net flows are so highly variable, this is not surprising. Taking quarterly averages may be appropriate in much the same way as moving averages are often used to filter out "noise" in volatile series.

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period, however, experiments with disaggregating by time suggested that the determinants of the net flow were significantly different in the later years. The time frame from 1976-1983 was chosen because by 1976 the program, more-or-less as it is known today, was well established. In addition, there was a not insignificant practical consideration. Prior to 1976 there is a substantial amount of missing data on food stamp participation.[1] Some states initiated a program later than others, or delayed moving toward coupon issuance rather than commodity distribution. While observations with missing data may be eliminated from the sample for the purpose of regression under certain conditions, the data requirements are far more restrictive for the technique we employ to account for temoral and geographic variation in our data -- so-called "error components" technique which is appropriate for pooled cross-sectional and time series data.[2] Thus, combining program knowledge with practical considerations, we decided to analyze the model from 1976-1983 in order to test our final set of hypotheses and to draw policy implications; data from 1970-1983 were useful for preliminary analysis.

Appendix Tables B.1-B.4 contain descriptive statistics on the varibles used in analysis for both time periods. A point of interest is the difference in the average net flow between the two periods. Between 1970 and 1983, the average stood at +1,983 cases but was only +831 cases between 1976 and 1983. A standard test of the difference between two means indicates that this drop

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1. In four quarters, data are missing for all states -- 1970:Q3, 1971:Q3, 1972:Q4, 1973:Q1.

2. Even over the period from 1976-1983, Alaska had so many missing reports on food stamp participation that we dropped Alaska from the analysis entirely for the purpose of presenting our final regression and error components results.

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is significant; the average net flow was indeed lower during 1976-1983.[1] In contrast, AFDC case openings and case closings appear to have been higher, on average, during 1976-1983 than over the total time period.[2] Of course, it is more difficult to separate out population growth effects on a variable like case openings (or closings) than the net change in the caseload, which abstracts to some degree from the absolute level of the caseload. The population figures confirm, as expected, that, on average, the population is larger and slightly older during 1976-1983.

With the exception of average social security benefits, real benefit levels were relatively unchanged over the period of analysis. Nominal benefits are all higher, on average, during the period from 1976-1983, but real benefits are unchanged, on average, as compared to statistics calculated over 1970-1983. One final note, over the full period of analysis four business cycles occurred, while only two cycles occurred during 1976-1983. (See Appendix Table A.1).

Plots of the net flows at the national and regional levels reveal some interesting points. Figure 1 shows the net change in food stamp cases over the entire period for which data are available. Several salient points can be made. First, there is a slight tendency for more negative net flows to occur

1. For this test we compute,

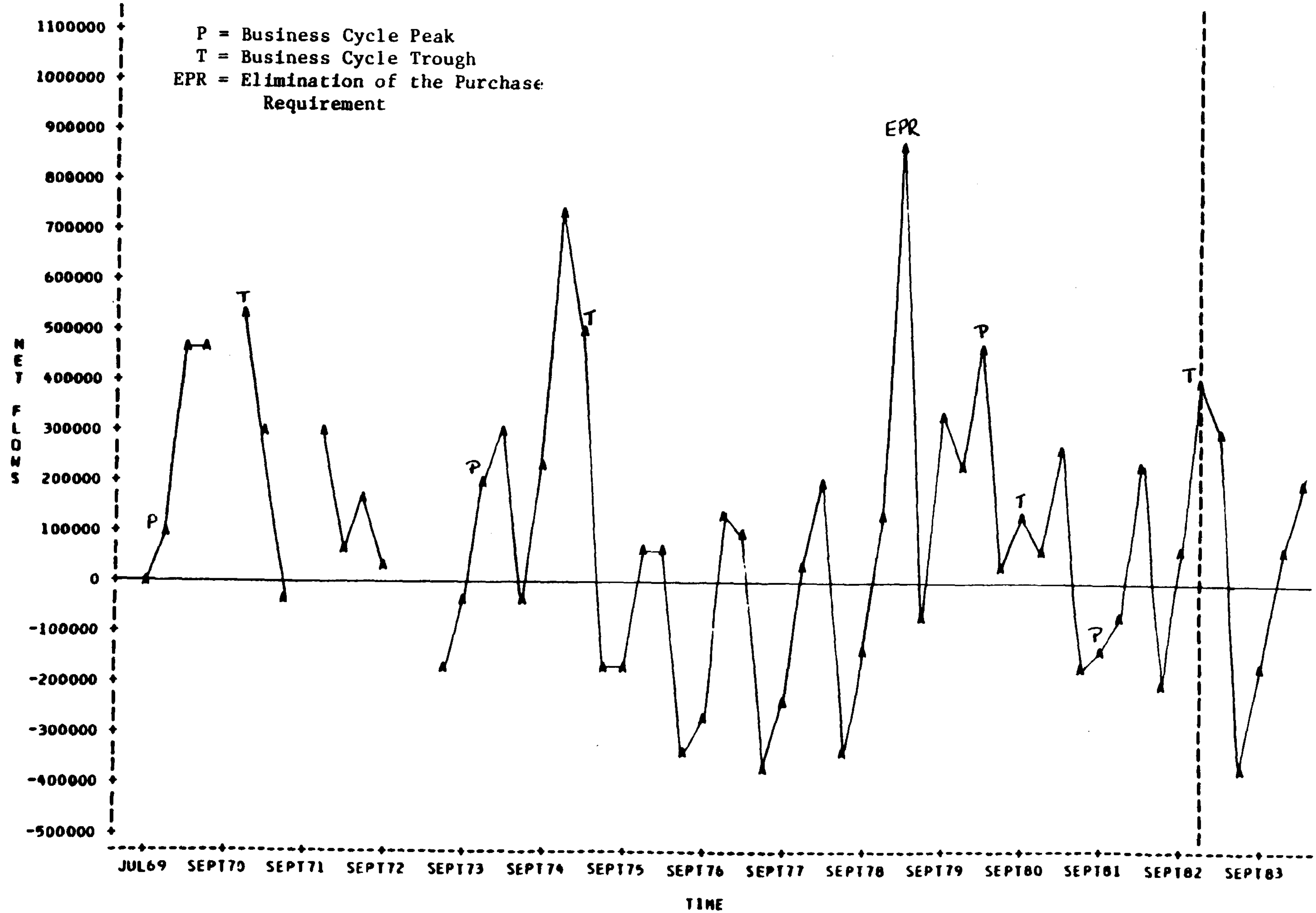
$$z = \frac{(\bar{X}_1 - \bar{X}_2) - 0}{\sqrt{\frac{\sigma_1^2}{N_1} + \frac{\sigma_2^2}{N_2}}} = \frac{(1983-831) - 0}{\sqrt{\frac{10665^2}{2596} + \frac{9545^2}{1600}}} = 3.6,$$

which is greater than the critical value of the z score at the .99 level (critical $z = 2.58$).

2. This difference is significant only at the .90 level.

Figure 1

PLOT OF NATIONAL NET FLOWS BY TIME



NOTE: Plot is interrupted where missing data occur.

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in the years since 1975, although the pattern is not absolutely clear due to missing data in earlier years. Second, the volatile nature of the series is visually underscored. The two major increases in the net flows are in 1974:Q4 and 1979:Q1; the former is associated with the general economic slowdown, as well as nationwide expansion, the latter with the elimination of the purchase requirement. Third, the relationship between changes in the caseload and the business cycle is not entirely as expected. There is a tendency for the net flow to be increasing when the cycle is moving toward a trough. This is as expected; business conditions are at their worst and program participation is growing. Note that the net flows drops off immediately after passing through the trough. On the other hand, there is also a tendency for program participation to be growing as business conditions move toward a peak, although the rate of growth is less than that heading toward a trough. One exception is the peak which occurred in mid-1981. Over the first two cycles the program was not well established. In the 1980 cycle the peak occurred within the same year as EPR, which may have had some impact continuing through the business cycle. In 1981 the net flows were indeed negative at the peak of business conditions, as one would expect.

The national net flows were disaggregated by region and those plots are displayed in Figures 2 through 8. The degree to which the national pattern is repeated for each region is surprising. There is really very little variation at the regional level -- supporting our later finding that there are no significant regional effects in the net flows model. In New England, Mid Atlantic, Southeast, and to some extent, the Midwest regions, the 1974 economic downturn exerted relatively more upward pressure on the caseload than

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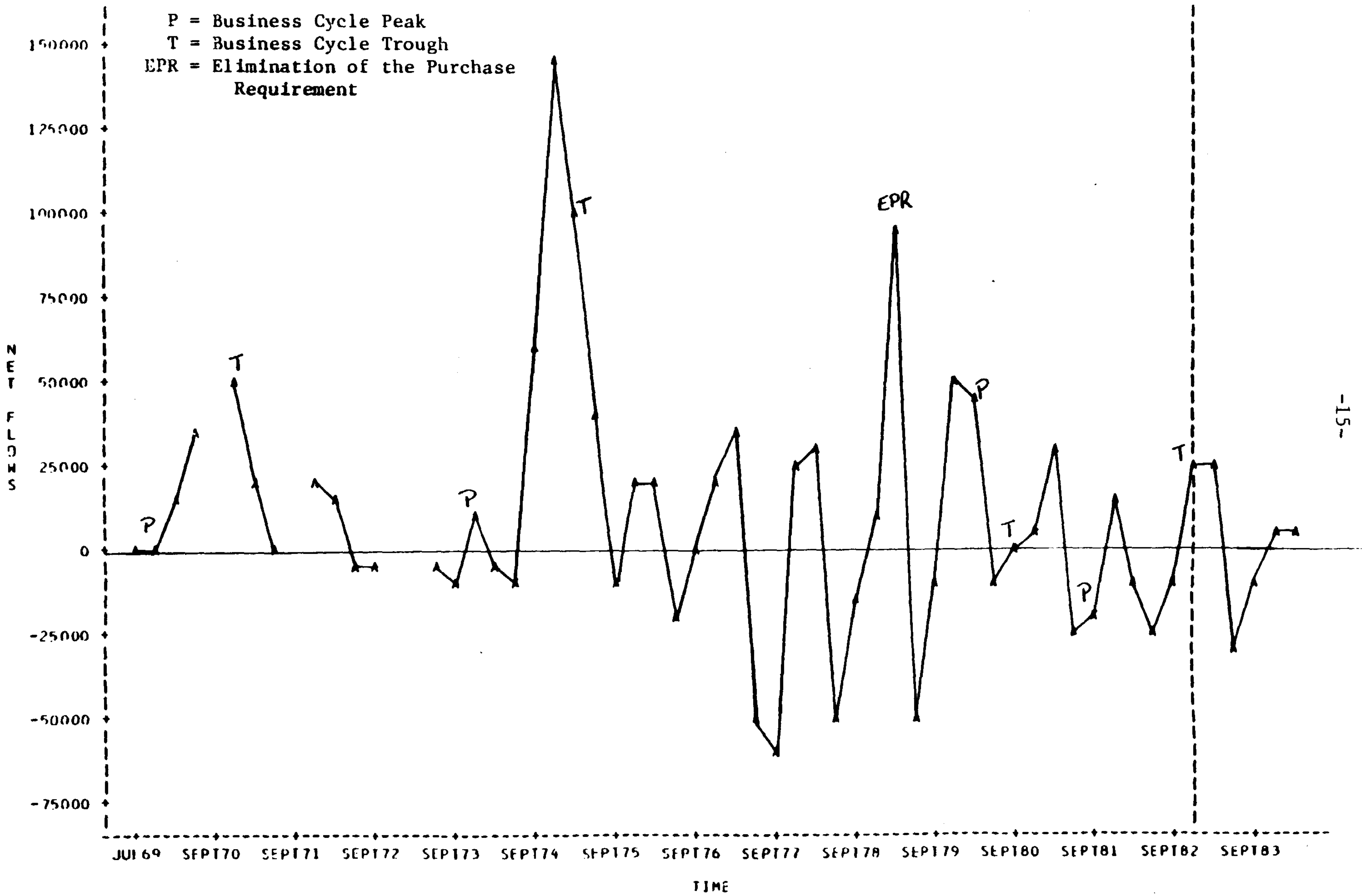
Figure 2

PLOT OF REGIONAL NET FLOWS BY TIME

NEW ENGLAND



NOTE: Plot is interrupted where missing data occur.

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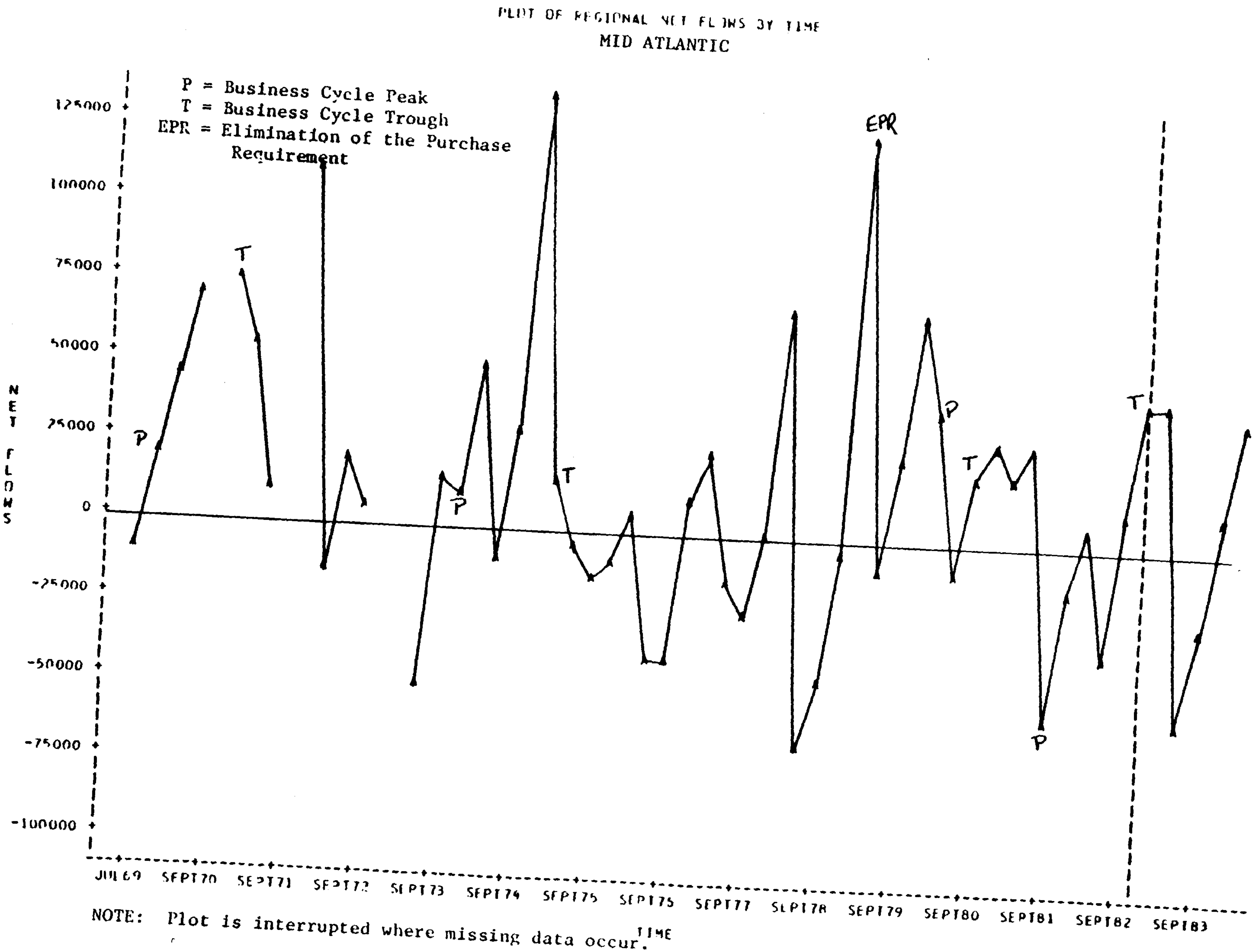
Figure 3

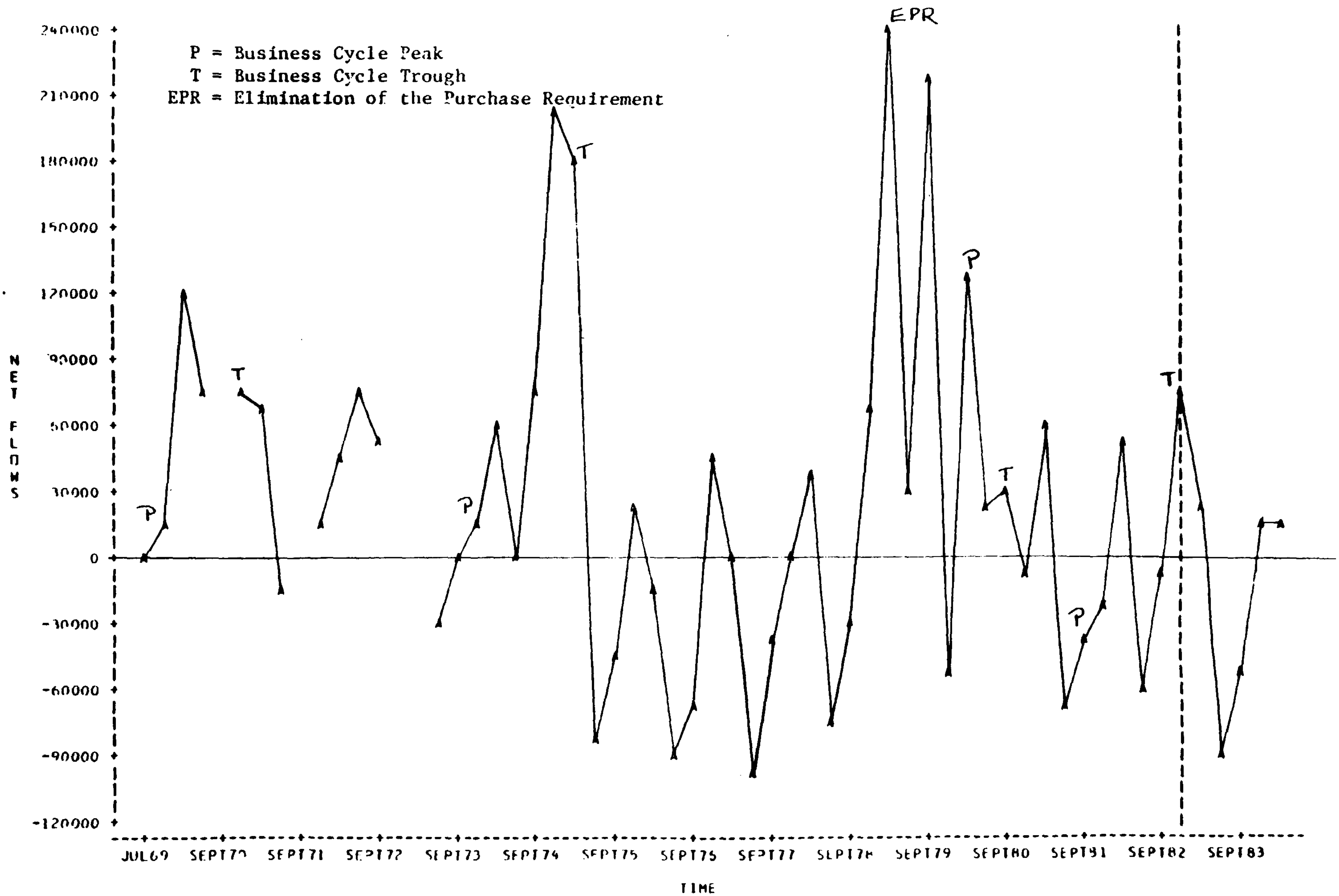


NOTE: Plot is interrupted where missing data occur.

Figure 4

PLOT OF REGIONAL NET FLOWS BY TIME

SOUTHEAST



NOTE: Plot is interrupted where missing data occur.

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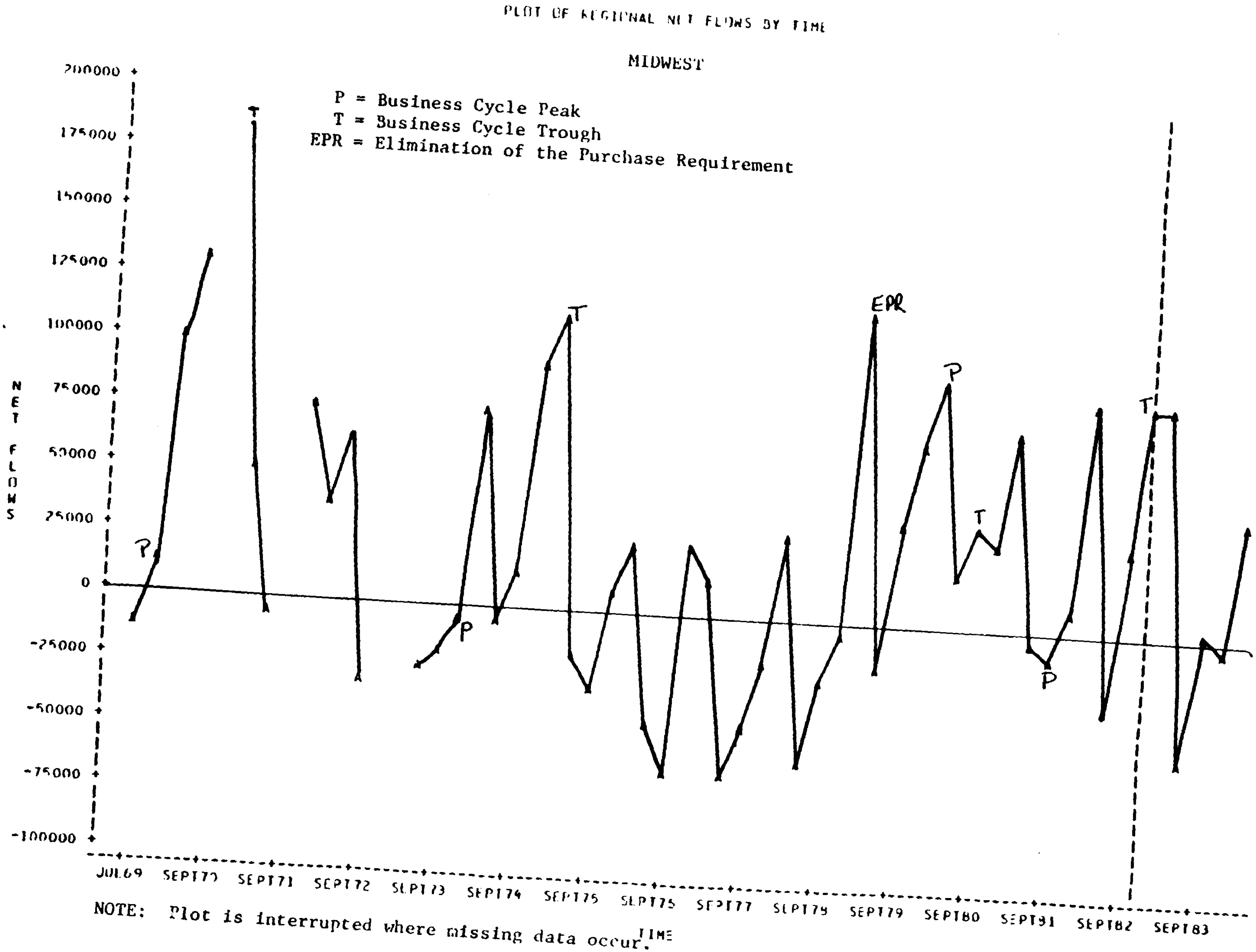
Figure 5



NOTE: Plot is interrupted where missing data occur.

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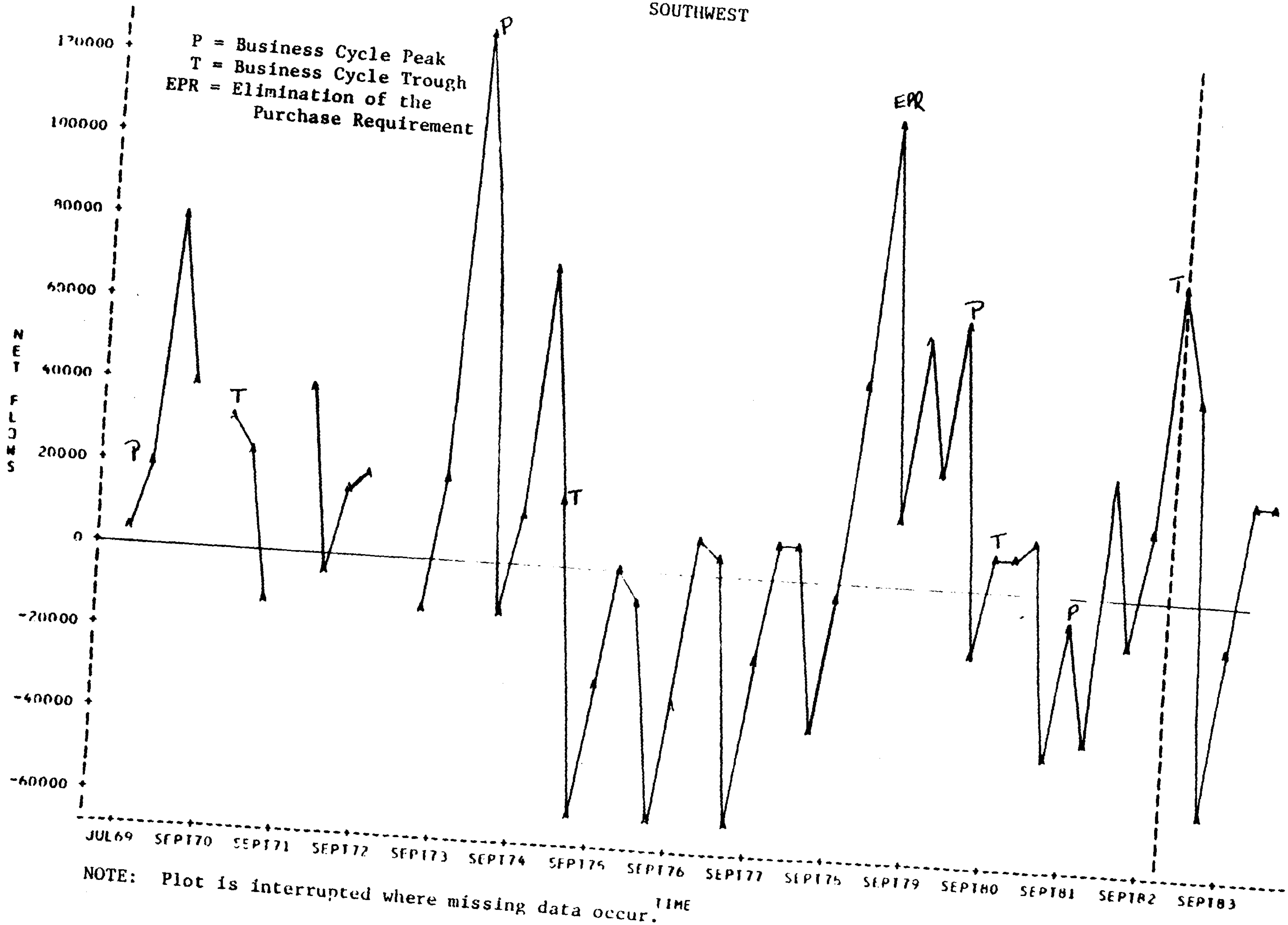
Figure 6

PLOT OF REGIONAL NET FLOWS BY TIME

SOUTHWEST



NOTE: Plot is interrupted where missing data occur.

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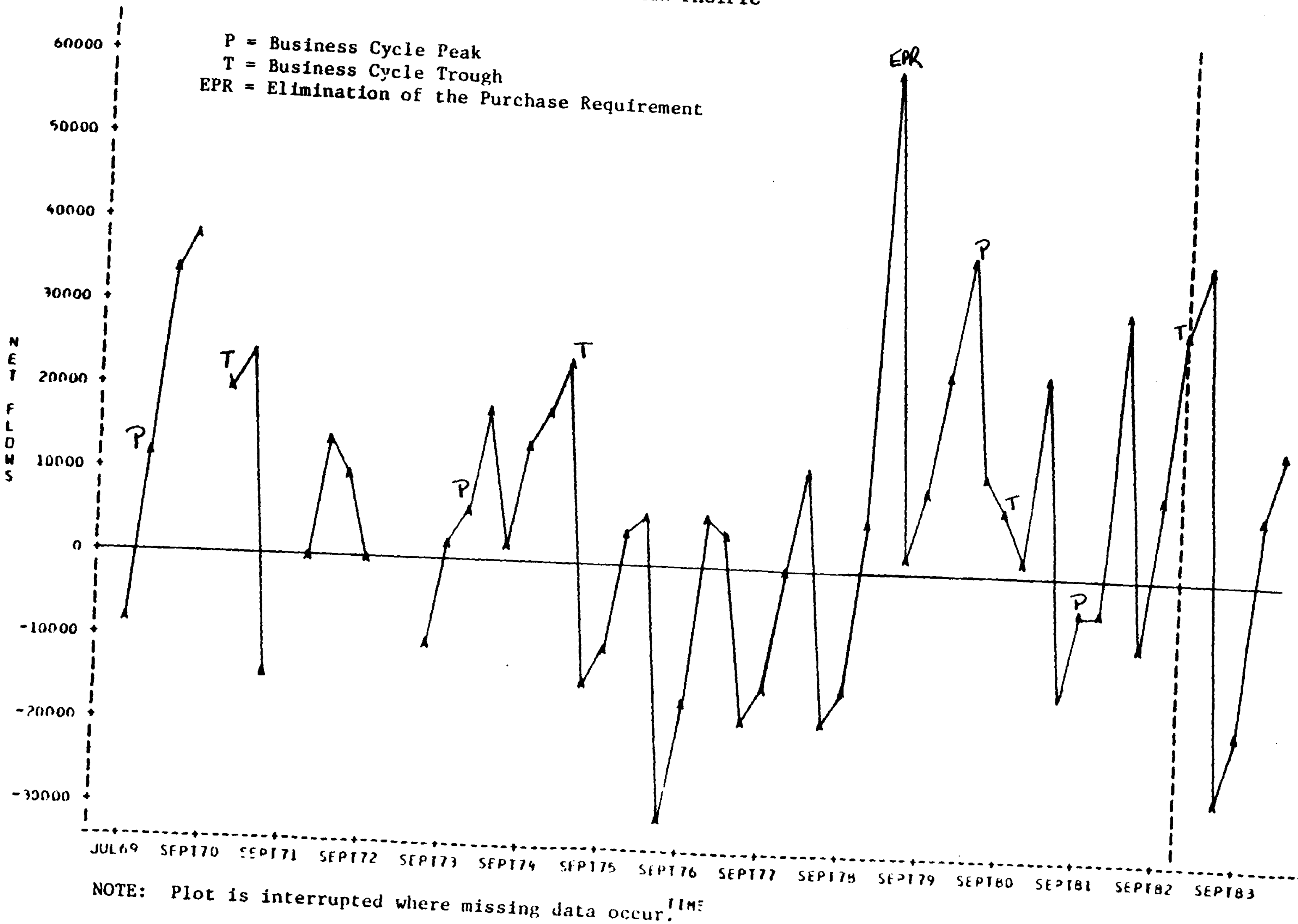
Figure 7

PLOT OF REGIONAL NET FLOWS BY TIME

MOUNTAIN PACIFIC



NOTE: Plot is interrupted where missing data occur.

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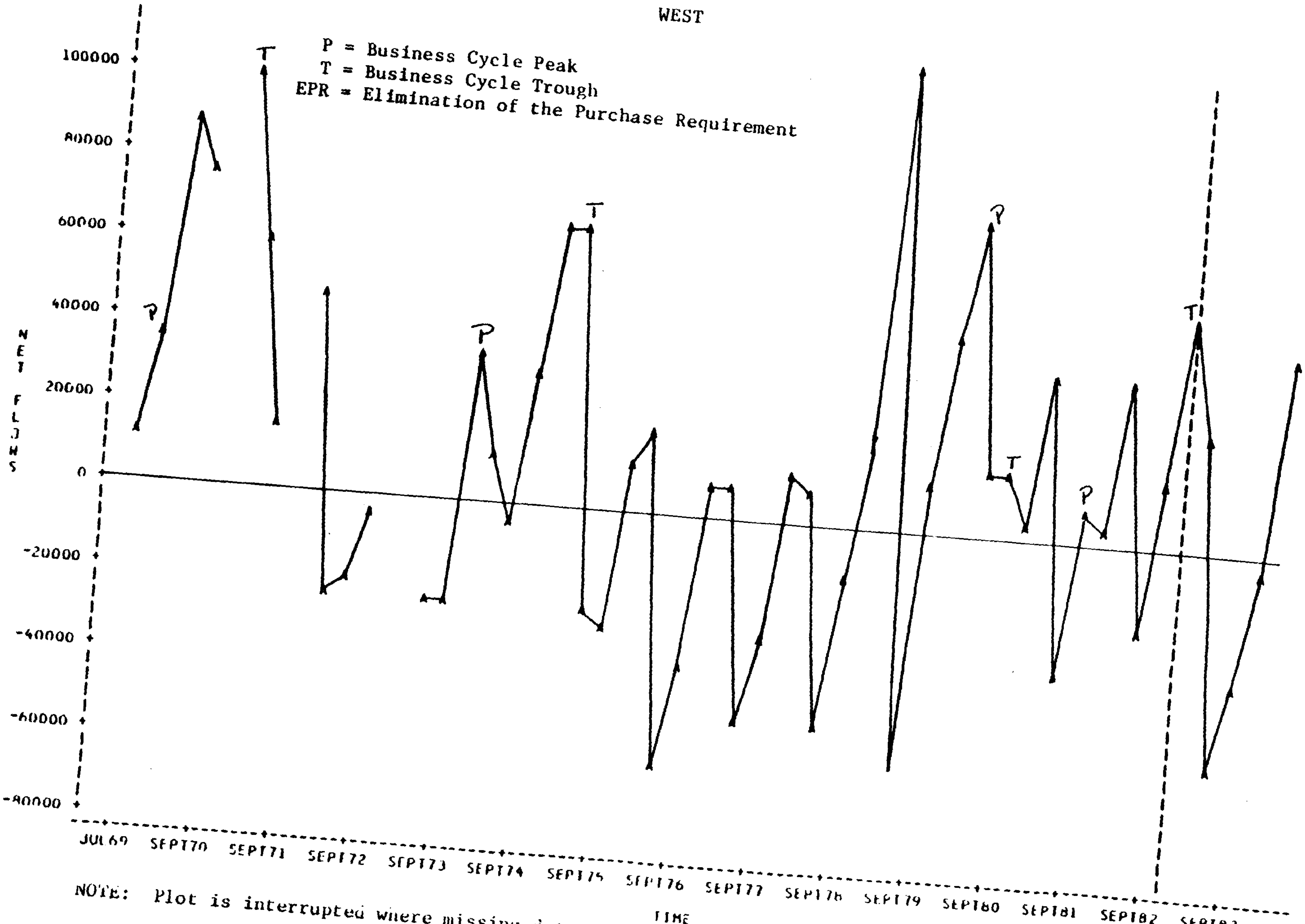
Figure 8

PLOT OF REGIONAL NET FLOWS BY TIME

WEST



NOTE: Plot is interrupted where missing data occur.

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in the western regions -- even more upward pressure than the EPR. The Midwest appears to have reacted sharply to the 1970 downturn. The Southwest exhibited an unusually large growth in the net flows in 1973:Q4 which happened to coincide with the peak of the business cycle. Tracing the source of this effect, we founa that Texas experienced tremendous program growth during this time as that state initiated a systematic program. Apart from these minor observations, there is little difference between the behavior of the net flows at the national and regional levels, -- a point that is itself significant to note.

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IV. Overview of the Empirical Analysis

In this section we present and discuss ordinary least squares (OLS) estimates of the coefficients and their t statistics associated with the "net flows" model for the period 1976-83. Recall that the conceptual model is as specified earlier, namely,

$$\ell_t = a_o + b_1 x_t + b_2 x_{t-1} + \ldots + b_k x_{t-k} + \varepsilon_t. \qquad (9)$$

For the purpose of preliminary analysis, we impose the assumption that the error term is distributed normally with mean zero and constant variance. Under this assumption, it is appropriate to employ OLS regression techniques to estimate the unknown parameters. This assumption is relaxed in subsequent model development.

The development of the empirical model actually followed a series of steps in which we experimented, using OLS regression, with a set of explanatory varibles, alternative functional forms, and using different definitions of the time period of analysis. As a final step we replace the error term with one characterized by an error components structure more appropriate to the pooled cross-sectional and time series nature of the data. The steps in the development of the final form of the net flows model are described in the next section.[1] For the moment, however, we present the main findings of our preliminary statistical analysis in order to summarize and give an overview of the marginal effects of changes in key economic,

1. We take this unusual approach in presenting the full range of empirical results primarily because this report serves as documentation of work done under contract to the Food and Nutrition Service. FNS staff expressed interest in details of the model development and we intend to be responsive to their request.

demographic, and program variables on the net change in food stamp caseloads.

The dependent variable in the regression analysis is the quarterly average of the month-to-month change in the state food stamp caseload of individuals. Our data are pooled cross-sectional and time series observations; quarterly state-specific program information is combined with exogenous data on economic and demographic characteristics and pooled over the time period from 1976:Q1 to 1983:Q4.[1]

The independent variables in our analysis fall into several major categories. In principal, the change in the food stamp caseload at any time t is a function of economic conditions, demographic characteristics of the population, and program parameters, including characteristics of programs highly related to the food stamp program, such as AFDC. Because the change in caseload at any time t is the net of case openings and case closings, we must consider as explanatory variables those factors which affect the pool of eligible participants in the current period as well as in previous periods. For example, the number of case openings may be a consequence of current AFDC case openings, demographic factors, seasonal factors, and program rules. In addition, we would expect current and lagged economic conditions to be important determinants. The food stamp caseload is known to be sensitive to the business cycle, and employment characteristics in particular. High levels of current unemployment are expected to affect case openings with a lag as people exhaust unemployment insurance coverage and personal savings. Hence,

1. We would like to emphasize the point that the pooled cross-sectional, time series nature of the data may present some special problems in the estimation. We discuss the problems and propose a correction using the "error components" method in a later section. We also address the question of the choice of time period in subsequent discussion.

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we would hypothesize that it is important to control for contemporaneous as well as lagged economic conditions.

Finally, in a pooled model of this sort, regional and time-related differences should be taken into account. The data measure caseload flows across all the states (except Alaska) and it is reasonable to hypothesize that regional effects, not captured by differences in other variables included in the model, may be present. Similarly, serial effects are often hypothesized in time series models of this sort--dummy variables for each year represented in the data (except 1976 which is the omitted dummy) are included. The hypothesis here would be that there are factors operating differentially upon caseload flows across time, that are unrelated to differences in economic, demographic, and program variables included.

Of major interest in the analysis of the net flows model is the impact of various program policy changes, particularly changes under 1981 and 1982 OBRA legislation. States implemented the various policy changes at different times, but, given enough variance in implementation dates, we can estimate the marginal impact of a policy change on the net flow of cases, holding constant economic and demographic conditions.[1]

From Table IV.1 it appears that there are no significant regional effects in the net flows model. On the other hand, the population age distribution is of some importance. If the state population under five increases by 1,000, we can expect a net addition of 17 people to the caseload (population variables are measured in millions); an increase of 1,000 people 18 to 44 will increase the net flow by 2. In contrast, increases in the age groups of 5 to 17 and sixty-five and older have a significant negative impact on the net flow. For

1. The extent to which we can disaggregate the impact of various changes implemented under the 1981 and 1982 OBRA legislation is potentially problematical. We discuss this point further in a subsequent section.

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Table IV.1

Ordinary Least Squares Estimates
1976-1983
N = 1600

Dep. Variable: Net Flow R^2 = .31

Variable	Parameter Estimate	t ratio
Intercept	-16320.2	-1.4
M. Atlantic	-301.0	-0.3
Midwest	-112.9	-0.1
Southwest	-502.1	-0.4
Mt. Plains	236.1	0.3
Western	-858.6	-1.0
Southeast	-129.9	-0.1
POP UNDER5	16882.6	2.6**
POP 5-17	-10401.9	-2.6**
POP 18-44	2279.2	2.2**
POP 45-64	6250.2	1.2
POP 65 PLUS	-6918.3	-1.8*
EPR	14872.9	4.8**
OBRA 81	963.9	0.6
OBRA 82	-864.1	-0.4
PROJECTS	-6.8	0.7
MAX FSBENR	68.7	2.4**
AFDC OPEN	0.8	9.6**
AFDC CLOSE	-0.8	-10.5**
MAX AFDCBENR	-3.8	-0.9
AVG SOCSECR	2.8	0.1
AVG SSIR	-7.5	-1.2
BC PEAK	6155.5	1.7*
BC TROUGH	-5368.7	-1.7*
PEAK LEAD	-1728.5	-1.7*
TROUGH LEAD	-646.6	-0.6
YPCAPR	-156.7	-0.5
URATE	2573.3	10.8**
IURATE/URATE	6082.8	3.3**
URATE(-1)	-2453.9	-10.4**
URATE*PEAK	-697.3	-1.4
URATE*TROUGH	896.0	2.6**
1977	715.2	0.8
1978	1807.8	1.9*
1979	-5506.5	-1.7*
1980	-12516.4	-3.8**
1981	-14093.4	-4.2**
1982	-14543.2	-4.0**
1983	-13661.9	-3.2**

**Significant at the .95 level or better.
*Significant at the .90 level.

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every additional 1000 people 5 to 17 the net flow drops by 10. For persons 65 or older the decrease is by 7. While we have no strong a priori notions regarding age effects, it seems reasonable that very young populations tend to increase the net flow since a large part of the poverty population is composed of children under 18 years of age.

It is interesting to note, however, that while 18 to 44 year olds have a slight positive impact on the net flow, the elderly appear to have a negative impact. This might suggest that food stamps are relatively less used by the elderly, who may rely on other sources, or, those eligible may have lower participation rates than younger persons, particularly family groups.

Changing economic conditions can be expected to have an important effect on the net flow. In the downturn of a business cycle unemployment rates are presumably rising. In a protracted slump spells of unemployment become lengthier. People exhaust unemployment insurance benefits and become eligible for food stamps. Hence, as economic conditions become worse, we would expect more cases to be opened than closed and the net flow to be positive. The exact opposite can be expected in boom periods. We control for changing economics in several ways. First, dummy variables representing the peak, trough, and quarters leading the peak or trough are included in the model.[1] Also included in the analysis is an interaction term betweem the state unemployment rate and the business cycle peak or trough. These terms test the hypothesis that business cycle effects vary depending on the rate of unemployment. The results here are somewhat anomolous. From the negative sign on the coefficient associated with the interaction between the

1. Two business cycles are recorded between 1976-1983. The first cycle peaked in January, 1980 and the trough occurred shortly thereafter in July, 1980. The next peak was achieved in July, 1981, followed by a protracted downturn with the trough in November, 1982.

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unemployment rate and the peak of the business cycle, we would have to infer that the higher the rate of unemployment during the peak of a cycle, the more negative is the net flow. While we would expect a negative net flow during the peak, we would not expect the net flow to become more negative, the higher the unemployment rate. Over the period from 1976-83 the average unemployment rate stood at 7.2%; the maximum during a peak was 11.2% while the average rate during a peak was 6.7%. From the model, the marginal change in the net flow for each of these two circumstances would be:

$$\Delta NF = 6155 - 697\ (11.2) = -1651$$
$$\Delta NF = 6155 - 697\ (6.7) = +1485$$

These results are counterintuitive. Note, however, that the coefficient on the interaction term is not significantly different from zero. Nonetheless, it remains that the coefficient on the dummy representing the peak of a business cycle is positive and significant at the 90% level, suggesting that the net flow is increased, on average, during the peak. Leading the peak, on the other hand, the negative coefficient (significant at .90) indicates a reduction in the net flow during the months prior to the official peak.

Our results are more intuitively appealing with respect to the business cycle trough. The coefficient on the interaction term between the unemployment rate and the trough is highly significant and is in the expected direction, overwhelming the seemningly anomolous negative coefficient on the trough dummy. During 1976-83 the maximum unemployment rate during a trough was 16.2%, while the average was 8.3%. The over-all effect on the net flow for these two circumstances is as follows:

$$\Delta NF = -5369 + 896\ (16.2) = +9146$$
$$\Delta NF = -5369 + 896\ (8.3) = +2068$$

Thus, given the typical experience with unemployment during this period, the model predicts a net increase in the food stamp caseload during the trough of

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a business cycle; that increase is greater the higher the rate of unemployment. While the coefficient on the trough dummy is negative, an unemployment rate below 6% is required before the over-all effect on the net flow is negative. In summary, the results with respect to business cycle effects are somewhat anomolous, especially the response of the caseload during the peak of a cycle. However, as we show in the discussion below, it is difficult to avoid intertwining business cycle and labor market effects. When the two are considered together, the results are quite sensible.

The specification of the unemployment rate in the model is somewhat complicated, and results from a series of experiments with alternative specifications are described in more detail in a later section. The unemployment rate (URATE) is specified to have an independent effect on the net flow, to interact inversely with the insured unemployment rate (IURATE) and directly with the peaks and troughs of a business cycle, and, finally, to have a lagged effect on the net flow. The over-all effect of a marginal change in the URATE can be expressed as,

$$\frac{\partial \text{ Net Flow}}{\partial \text{ URATE}} = 2573 - 697 \text{ (Peak)} + 896 \text{ (trough)} - 6083 \left[\frac{\text{IURATE}}{\text{URATE}^2}\right]$$

At sample means for URATE and IURATE, and ignoring business cycle conditions for the moment,

$$\frac{\partial \text{ Net Flow}}{\partial \text{ URATE}} = 2573 - 6083 \left[\frac{3.7}{7.2^2}\right] = +2139.$$

Note that the marginal effect of a change in the unemployment rate is nonlinear in nature. The higher the <u>level</u> of the unemployment rate, the

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greater the increase in net flows when URATE increases at the margin.[1]

There are several other interesting features of this specification. First, the marginal effect of a change in URATE varies depending on the level of the insured unemployment rate. Obviously IURATE and URATE tend to move in concert, but for a given rate of unemployment, more people are likely to be receiving unemployment insurance benefits if the spell of slack labor market conditions has been relatively short. In this case, we would expect the impact on the food stamp case to be somewhat muted. Thus, we include the ratio IURATE/URATE to test that hypothesis. The results are supportive. As IURATE rises, holding URATE constant, the net flow is reduced -- or, more precisely, the addition to the net flow is reduced.

Second, as we have already seen, the marginal effect of a change in URATE varies if we are at the peak or trough of the business cycle. At the peak of a cycle the increase in net flows is somewhat muted -- an increase in the unemployment rate results in a net addition to the caseload, but a smaller addition than would be the case at other points in the business cycle. On the other hand, at the trough of a cycle a small increase in URATE results in an even greater increase in the net flow.

Finally, our results suggest that a change in the unemployment rate operates with a contemporaneous and lagged effect on the net flows. The coefficient on URATE lagged one quarter is negative and highly significant. The interpretation here is that the direction of change in unemployment rates is of some importance. Holding current URATE constant, an increase in the lagged URATE has a negative impact on net flows. That is, abstracting from the level of unemployment rates, if the rate is falling there is a tendency

1. The second derivative of the equation with respect to URATE is positive indicating that the net flows increase at an increasing rate given a change in URATE.

toward a reduction in the net flow; if the rate is rising there is a tendency toward an increase in the net flow. This result can be seen most easily by simply comparing the coefficient on current URATE (+2573) to that on lagged URATE (-2454). The two coefficients are almost equal, therefore, if the rate was higher in the past (i.e., rates are falling) the net effect in the present is slightly negative, and vica versa, if the rate was lower in the past (i.e., rates are rising)[1]. In summary, our analysis suggests that unemployment conditions are important determinants of changes in food stamp caseloads, and changes in the rate of unemployment impact the net flow in a complicated fashion. In general, as the unemployment rate rises, there is a net increase in food stamp cases. However, this increase is muted (1) the lower the level of URATE, (2) the higher the insured unemployment rate, or (3) if a peak in the business cycle is achieved. Lastly, if unemployment rates are rising through time, there is an even greater tendency for the net flow to rise in the face of a fixed percentage increase in URATE.

The last economic control included in the model is deflated per capita personal income (YPCAPR).[2] We hypothesize that, holding constant business cycle and labor market conditions, the higher the level of per capital real income, the lower the net flow of food stamp cases. The estimated coefficient is in the right direction and suggests that for every $1000 increase in per capita real income, there is a net reduction of 157 food stamp cases.

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1. The standard errors of the coefficients both round to 237, and we are unable to reject the hypothesis that the two coefficients are equal. Keep in mind, however, that this partial analysis ignores other terms in the model involving URATE and over-simplifies the net effect of a marginal change in contemporaneous unemployment rates.

2. All money variables in the model are deflated to reflect the hypothesis that it is changes in real income (or benefits, etc.), rather than monimal measures, that affect caseload flows. See Appendix Table A.1 for a definition of the deflated variables.

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However, the standard error is more than twice the size of the coefficient and it is not statistically significant.

Key to the analysis is the role played by program parameters in the net flows model. To some extent participants in programs like AFDC and SSI are likely to participate in food stamps because the criterion to qualify are similar. The constituency is not identical, however, for a myriad of reasons. Two highly related programs are AFDC and food stamps; this point is borne out in our model. AFDC case openings and closings are entered separately as explanatory variables to see if the opening of an AFDC case has any different effect on the net flow of food stamps than the closing of an AFDC case. The estimated coefficients are almost identical and in opposite directions, as would be expected. Hence, the marginal positive impact on food stamp caseloads of an AFDC opening is equivalent to the marginal negative impact of an AFDC closing.[1]

Estimating the order of magnitude of the AFDC effect is less straightforward. AFDC data are measured quarterly, hence, the distribution of a quarterly change on the monthly food stamp net flow is about one-third the estimated coefficients.[2] This would suggest that for every four AFDC cases opened (closed), the food stamp net flow is increased (decreased) by one. The correspondence between programs would seem to be less than expected, but it is important to keep in mind that the interpretation of the marginal effect of a case opening or closing on the <u>net flow</u> of food stamp cases is less

1. A potentially superior specification would be to calculate the net flow of AFDC cases and use that measure instead of AFDC case openings and case closings. The interpretation would be more straightforward.

2. The independent variable is case openings in a <u>quarter</u> while the dependent variable is average net flows in a <u>month</u>. We can assume that cases are opened evenly across the three months in a quarter and that one-third of the total impact is felt each month. This is a simple monotonic transformation of the independent variable and the estimated coefficient; divide the coefficient by 3 to estimate the monthly effect.

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straightforward than if we were estimating food stamp case openings (closings) as a function of AFDC case openings (closings).

Program benefits are also included in the analysis, however, the expected direction of the effects of different program benefits is somewhat ambiguous. For food stamp benefits the direction is clear. On balance, we would expected an increase in legislated benefits to increase the net flow of cases, ceteris paribus. To test this hypothesis we include the maximum food stamp benefit for a family of four in our model. As are all money variables, we express this variable in "real" terms to avoid the problem of money illusion. That is, money variables tend to increase through time due to the effects of inflation. If there is a serial tendency in the dependent variable of a regression, a causal relationship may be assigned that is really nothing more than a statistical artifact. Hence, the maximum food stamp benefit for a family of four is divided by the CPI for food at home, since we would argue that it is changes in food prices (rather than the general price index) that determine the purchasing power of food stamp benefits.[1] We include maximum legislated benefits rather than average actual benefits because the former is not affected by program participation, and it more clearly measures fixed program parameters. Our results indicate that there is a positive and statistically significant relationship between maximum food stamp benefits and the net flow. For each real dollar increase in benefits the net flow is increased by about 69 people.

Deflated values for maximum AFDC benefits for a family of four and average SSI benefits for an aged couple were included in the analysis, in

1. Maximum benefits do not vary across the states but they do vary through time -- largely reflecting adjustments in the price of the Thrifty Food Plan. By deflating according to the CPI for food we do introduce regional variation in benefits for any given quarter.

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part, to capture the effects of "generosity" in other transfer programs on changes in the food stamp caseload.[1] However, income received from these programs can be counted when checking for food stamp eligibility. A priori, the direction of the effects with respect to these programs is ambiguous. Our estimates suggest a negative but insignificant relationship between the AFDC and SSI program benefits and food stamp caseload changes. Finally, average social security benefits are included primarily to see if there is some type of income effect on food stamp participation. Again, the coefficient is insignificant.

The program measures of most interest in the analysis are the dummy variables reflecting major legislative changes. These include the elimination of the purchase requirement (EPR), the 1981 OBRA changes, and the 1982 OBRA changes. EPR, as one would expect, had a dramatic impact on the food stamp caseload. In most states the purchase requirement was eliminated in December, 1978 or January, 1979, with a couple of states implementing in February, 1979. Since people were no longer required to buy discounted coupons, there was an immediate increase in the number of eligibles electing to participate.[2] From the OLS model our preliminary estimate is that approximately 14,873 individuals were added to the monthly net flow of food stamp cases after EPR was implemented. The coefficient is statistically significant at the .99 level. Keep in mind that this figure represents a short-run average response at the state level (14,853 * 51 = 78,523 implied at the national level); we are not attempting to model the long-run effects of EPR.

1. These variables were all deflated by the CPI for all items rather than food since these programs are not targeted to food assistance. We use Average SSI (not including State supplements) because the maximum series is not published.

2. This point is emphasized in later descriptive analysis and is visually confirmed in graphs of the change in caseloads.

The Omnibus Budget Reconciliation Act of 1981 (1981 OBRA) and Food Stamp Commodity Distribution Amendments provided for several key program changes:

a. The adjustment of the basic benefit for changes in the ccst of the Thrifty Food Plan was delayed from January, 1982 to October, 1982.

b. The income eligibility test was switched to a gross income standard equal to 130 percent of the poverty guidelines.

c. First month's benefits are prorated from the date of application.

d. New provisions eliminating strikers and the treatment of boarders.

e. The earned income disregard is lowered from 20 percent to 18 percent of earnings.

f. Repeal of increases in dependent and medical care deductions.

These provisions were not implemented by all states at the same time. From information provided by FNS, however, implementation for new cases began in the period from October, 1981 through January, 1982.[1] A dummy variable was used in the analysis and set to one in the quarter (and all subsequent quarters) in which the state indicated that new case conversion began for most provisions, especially the gross income provision. Of course the postponement of the benefit adjustment is not reflected by this dummy variable, rather, it is picked up by the maximum benefit variable. The estimated coefficient on the 1981 OBRA dummy variable is approximately 964, but the standard error is 1491 making the estimate not significantly different from zero. Hence, we

1. We elected to measure "implementation" from reports on new case conversion rather than total caseload conversion. There appeared to be considerable variance in total conversion -- some states indicated a lengthy period from the point when new cases implemented a change to the point where the change was implemented for all cases.

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have no support for the claim that 1981 OBRA legislation had any impact on the net flow of food stamp cases.

The effects of the 1982 OBRA legislation are potentially more difficult to incorporate into our model. This is largely because the number of new measures which tall under the 1982 OBRA plan was very large, and, several major features were to be implemented at only marginally different times. We experimented with several modifications to the definition of 1982 OBRA legislation, which are described in a later section, and settled on the use of a single dummy variable equal to one after implementation of the following features:

a. Restricted guidelines as to the definition of a household.

b. Simultaneous net and gross income test.

c. Restrictions on eligibility of college students.

d. Expanded benefit receipt of disabled veterans.

e. Error rate penalties for states.

f. Restrictions on initial allotments.

In addition, expedited coupon issuance and assignment of standard utility allowances were being nearly simultaneously implemented and it would not be possible to assign separate effects. The only major feature of the 1982 OBRA plan not accounted for in this model is rounding down of household allotments and deductions. The estimated effects of rounding down are discussed later. The one percent reduction in the Thrifty Food Plan Adjustment is taken into account with the maximum food stamp benefit variable.

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As with the 1981 OBRA effect, we cannot claim support for the hypothesis that 1982 OBRA changes tended to reduce (or increase) food stamp caseloads. While the estimated effect on the net flows is negative, it is not significantly different from zero in a statistical sense.

As a final matter we need to discuss the coefficients associated with the dummy variables for the year (omitting 1976). Recall that the data are pooled cross-section and time series observations. In a later section we present results from an estimation procedure which take into account potential correlations across states or through time. In the regression analysis it is useful to control for serial effects as best possible. By inserting a dummy variable for each year (except one) we allow for a fixed effect (across states, that is) on the net flows that varies across years.[1] The estimated coefficients on these variables are generally significant, with the exception of 1977. For 1978 and 1979 the coefficients are significant at the .90 level; significance is at the .99 level in later years. The other striking result is that the estimates suggest a rather larger negative fixed effect in all years since 1979, ranging in magnitude from -12,516 in 1980 to -14,543 in 1982. For these years the effects are not very different from one another. In fact, judging from their standard errors, we could not claim that the coefficients are different from one another.

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1. We do not allow the effect to vary across quarters to conserve degrees of freedom and because this degree of generality is not that useful for analysis.

Year	Estimated Coefficient	Standard Error	t-statistic
1977	715	873	0.8
1978	1,808	969	1.9
1979	-5,507	3,281	-1.7
1980	-12,516	3,287	-3.8
1981	-14,093	3,341	-4.2
1982	-14,543	3,626	-4.0
1983	-13,662	4,246	-3.2

Since our regressions are controlling for economic and demographic factors, as well as major legislated program changes, it is interesting to speculate on the source of these recent negative effects on the net flow of food stamp cases. We delay discussion of this point, however, until after the statistical correction for the pooled nature of the data is taken into account.

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V. Development of the Net Flows Model

Development of the net flows model, of which OLS estimates were presented in Section IV, followed a step-wise procedure. In this section we discuss some of the major steps in the model development, ending with the assumption of an error components structure for the disturbance term. We began with a basic equation which took into account geographic, demographic, and simple economic phenomena, and enhanced this simple model to reflect hypotheses regarding the role of program characteristics, unemployment, the income distribution, and the like. While the discussion of the model development is of interest to the reader, we have chosen to highlight significant results rather than present a long series of regressions for comparison.

Basic Geographic and Demographic Effects

Very early experimentation with the net flows model included a specification comprised solely of FNS regional dummy variables, the population distribution, and business cycle dummy variables.[1] With this core set of explanatory variables, we are able to explain 9 percent of the variation in the net flows. There are no significant regional effects, even in this simple model, but business cycle variables are important. The coefficients for the trough and quarter leading the trough are positive and significant, as are the coefficients for the peak dummy variables. While the latter result is counterintuitive, it is not a major surprise given the discussion of the net

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1. The preliminary analysis was carried out using pooled data from 1970:Q1 to 1983:Q4.

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flow plots in the previous section. With respect to demographics, this simple specification suggests a significant positive impact associated with the population under five and a significant negative impact for the age group between 18 and 44.

Program Characteristics

Dummy variables representing the key legislative changes were added to the basic specification, raising the R^2 to .12.[1] EPR had a highly positive and significant impact on the net flow, but, more interesting is the fact that both 1981 OBRA and 1982 OBRA were estimated to have a significant negative effect. The addition of the legislative dummies also had an impact on the business cycle effects. The coefficient associated with the peak was still positive, but no longer significant, while the lead of the peak was estimated to have a negative (significant) effect; trough effects were unchanged.

Two other food stamp program measures were included -- the maximum benefit for a family of four (nominal terms) and the number of project areas. The former was included to test the hypotheses that program benefits exert a direct influence on the net flow. Surprisingly, the estimated coefficient was negative and significant at the .99 level, suggesting an inverse relationship between benefits and net changes in the caseload. As we point out later, this result is reversed when we re-estimate the model expressing all money variables in real terms. The number of food stamp project offices is included as a proxy for growth in the program. Over the

1. For EPR, 1981 OBRA, and 1982 OBRA the dummy variable was set equal to 1 in the quarter in which implementation took place, and all quarters thereafter. Refer to Appendix Table A.1 for more precise information.

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early years of the program, especially before 1975, the growth in project offices closely tracked the expansion of the program and the mandated switch from commodity distribution to issuance of coupons. Because some states actually reduced the number of projects in later years, we froze the measure at its maximum for our purposes. Unfortunately, the coefficient never proved to be significant and is always very small in magnitude.

Because 1982 OBRA changes were fairly complex, we estimated several alternative specifications. We had information on separate implementation dates of rounding down, standard utility allowances, expedited coupon issuance, and the remaining features lumped together as described in Section I. Unfortunately, with the exception of rounding down, there was not sufficient variation in implementation dates to estimate separate effects for the different features of the 1982 OBRA package -- all the activity seemed to focus around 1983:Q1. Rounding down was to be implemented earlier -- around 1982:Q4, which coincides precisely with the trough of the business cycle. Attempts to estimate a separate effect attributable to rounding down resulted in a coefficient that is highly positive and significant at the .99 level. At the same time, the coefficients associated with the business cycle trough are reduced in magnitude and become insignificant. Our hypothesis is that the effects of rounding down cannot be separated from the effects of the trough, and the coefficient is picking up the positive effect on the net flow that should be attributable to the trough. Certainly one would not expect rounding down to have a positive impact on the net flow. For that reason, we drop rounding down from the analysis.

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The addition of AFDC program variables has an interesting effect. First, the AFDC variables alone account for 10 percent of the variance in the net flows (the R^2 is raised from .12 to .22). Second, the coefficient associated with 1981 OBRA becóme insignificant (but still negative). Third, the population group from 5 to 17 is now estimated to have a significant negative impact while the sign for 18 to 44 year olds has flipped to positive (significant at .90). The latter result suggests a strong correlation between AFDC cases and certain population age groups -- an obvious conclusion for many reasons. It is more difficult, however, to provide a simple explanation for these particular changes in the population effects in terms of correlations with AFDC caseload changes. In any case, the population coefficients remain robust with respect to adding other explanatory variables to the specification.

Economic Controls

It is well known that economic conditions have a major impact on the changes in food stamp caseloads. One of the first economic "enhancements" we analyzed was to express all money variables in real terms and add the unemployment rate and per capita income. (See Appendix Table A.1 for a definition of the deflated variables.) The deflation procedure actually served to reduce the explained variance somewhat. Perhaps this is not surprising, since nominal measurements exhibit a clear serial tendency which tends to make the relationship through time between two variables appear more systematic than may actually be the case. In addition, certain other effects were observed. The marginal effect attributed to EPR, while still positive and highly significant, was reduced in magnitude considerably; the coefficient

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on 1981 OBRA becomes more negative and is significant at the .90 level. The unemployment rate was estimated to have a positive marginal effect, as expected, but the order of magnitude of this effect dropped considerably when the model was expressed in real terms. Real income per capita is estimated to have a significant negative impact on the net flow. Again, this result is in line with expectations -- as real per capita income in the state rises, ceteris paribus, fewer people join the food stamp program than leave the program, either through choice or failure to qualify. Finally, while the switch to real terms had little impact on the coefficient associated with maximum AFDC benefits (still not significant), the maximum food stamp benefit coefficient switched in sign from negative to positive and remained significant. This result would appear to lend support to the hypothesis that as the relative value of food stamp benefits increases, more eligible participants will elect to join the program (or fewer leave).

The next set of experiments focused on the role played by income, earnings, and the distribution of income. Largely as an alternative to per capita income, we included average weekly earnings in manufacturing (See Appendix Table A.1 for a precise definition). This variable had several potential advantages. First, it was available by state on a quarterly basis making it a "richer" variable in the sense that it would exhibit more variation. Second, we felt it more closely measured the income concept relevant to the food stamp program. On the other hand, the variable had a major disadvantage -- there were a significant number of missing observations. By including average weekly earnings, our sample size was considerably reduced and, although the coefficient was negative (as expected),

the coefficient was not significant. Thus, we abandoned weekly earnings in favor of per capita income.

While per capita income adequately measures average well-being, we hypothesized that the distribution of income should have an independent effect, in that the greater the proportion of people with very low incomes, the higher the net flow. Mean values for the income distribution series (calculated over the period 1970-1983) are presented in Appendix Table B.1. The vast majority of families earn incomes above $10,000 (constant 1983 dollars) -- on average, 86 percent of families. Just under 5 percent of families earn under $5,000. It is important to note that this variable has not changed drastically over the period from 1970 to 1983, nor is there much variation across the regions. Perhaps for this reason, the estimated coefficients associated with this series are somewhat unstable. When estimated over 1976-1983 they were never significant, which is why the variable is omitted in the final model. We found the coefficients to be significant over the 1970-1983 period, and the effects were positive for categories under $5,000, as hypothesized. Unfortunately, the effect was also positive and marginally significant for the income category of $20,000 or more and this result is counter-intuitive.

Perhaps the most interesting set of experiments centered around the specification of the unemployment rate (URATE). We wanted to test several hypotheses, including:

(1) The higher the URATE, the more positive the net flow -- slack labor market conditions force people to supplement with food stamps.

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(2) The impact of changing unemployment conditions is nonlinear, that is, a percentage increase in URATE at low levels of URATE has a lesser impact on the net flow that a percentage increase in URATE at high levels of that variable.

(3) For a given level of URATE, the higher the insured unemployment rate (IURATE), the less pressure on the net flow, i.e., the smaller the positive effect, since more people are able to rely on unemployment insurance to tide them over a spell of joblessness.

(4) The effects of a change in URATE vary depending on the business cycle due primarily to the role of individual's expectations. At the peak of a cycle, expectations would be that any bout of unemployment would be short-lived -- not worth the effort to establish formal eligibility for food stamps. At the trough of a cycle expectations for a reversal are poor because conditions are at their worst.

(5) The duration of unemployment has an effect on the change in food stamp case loads independent of the level of unemployment. As the average length of joblessness increases, personal resources are exhausted and people seek out assistance, including food stamps. (This hypothesis is related to #3).

To test these hypotheses we experimented with a host of URATE, IURATE, and nonlinear specifications before settling on the form shown in the final model. Several interesting points emerged from these experiments. First, the unemployment effects on the net flow are of the complex nature we hypothesized. We found support for hypothesized interactions between the unemployment rate and the insured unemployment rate, and the unemployment rate and the business cycle. In addition, changes in the URATE impact in a nonlinear fashion. We did not find support for the hypothesis that the

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average duration of unemployment, had an independent effect on the net flows -- at least using the percent distribution of duration of unemployment to test this hypothesis.

Incorporating Lagged Economic Effects

A distributed lag model is implied by the original conceptual framework (see expression 9). This was motivated by the fact that the current stock of eligible participants, on which the net flow is based, is partially a function of events which have occurred in the recent past. It is hypothesized that economic factors, in particular, may operate with a contemporaneous and a lagged effect. To test that hypothesis we included the unemployment rate lagged one, two, and three quarters. The results indicated that URATE lagged one quarter was a significant addition to the model and that there was an inverse relationship between the net flows and lagged unemployment.

The coefficients on the URATE lagged two and three quarters were declining in value, but were not significant. In addition, we tested a modification which included lagged interaction terms between the unemployment rate and the insured unemployment rate. These proved more difficult to interpret and we decided that a more straightforward specification which included a single lagged term for the unemployment rate was most defensible.

The strong negative coefficient on URATE (-1) defies straightforward interpretation. Our initial hypothesis was that lagged unemployment rates should impact the net flow in the same way as contemporaneous unemployment rates, but with a diluted effect. However, the strong negative coefficient on URATE (-1) suggests that the higher the unemployment rate in the previous quarter, the lower the current net flow. The key here may be in remembering

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that we must evaluate the coefficient on URATE (-1) HOLDING CONSTANT CURRENT URATE. That suggests that the interpretation hinges on how URATE has been changing through time. Given current unemployment conditions, an increase in previous levels of the rate of unemployment serves to reduce the net flow of food stamp cases in the present. That is, as the unemployment rate is falling through time, there is downward pressure exerted on the level of the current change in caseloads.

Finally, we also experimented with including lagged terms for real per capita income, but the coefficients never proved to be significant. One problem was the fact that per capita income is measured on an annual basis so we had to lag the variable four quarters to get any variation from the current measure. While this is not ideal, given our data constraints it was necessary. Even at that rate, the series shows only slight variation through time -- probably not enough to disaggregate between current and lagged effects.

Assumptions Regarding the Error Structure with Pooled Data

The question of the appropriate estimation technique is of special interest when the data consist of pooled cross-section and time-series observations. In this case the usual assumptions employed in OLS about the behavior of the disturbances are less likely to hold. Nor can we assume a simple autoregressive model, as in the case of most time series analysis, since the behavior of the disturbances over the cross-sectional units (states in our example) is likely to differ from the behavior of the disturbances of a given state over time. For example, some states are subject to more seasonal variation in caseloads due to the presence of migrant workers than other

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states. This relationship between the disturbances is quite different than the effect of, for example, a lengthy auto workers strike in Michigan.

We make use of the so-called "error components model" to take into account the behavior of disturbances with pooled data. The basic assumption is that the error term associated with the regression (ξ_{it}) is composed of three independent components -- one associated with time (t), another associated with the cross-sectional unit (i), and the third varying in both dimensions. Hence,

$$\xi_{it} = u_i + v_t + w_{it},$$

where

$$u_i \sim N(0, \sigma_u^2),$$

$$v_t \sim N(0, \sigma_v^2),$$

$$w_{it} \sim N(0, \sigma_w^2),$$

and

$$\text{var}(\xi_{it}) = \sigma^2 = \sigma_u^2 + \sigma_v^2 + \sigma_w^2$$

Given these assumptions, the net flows model is re-estimated using the method described by Fuller and Battese and implemented by Drummond and Gallant.[1] The estimated coefficients are unbiased and asymptotically efficient.

In Table V.1 we present the error components estimates. In general, the coefficients are little changed from those presented in Table IV.1, which were estimated using OLS, however, the standards errors are changed

1. See Fuller and Battese, "Estimation of Linear Models with Cross-Error Structure," Journal of Econometrics vol. 2, May, 1974 (pp. 67-78). Also see Drummond and Gallant, "TSCSREG: A SAS Procedure for the Analysis of Time Series Cross-Section Data," Institute for Statistics, Mimeograph Series No. 1107, North Carolina State University, February, 1977.

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Table V.1

Fuller and Battese "Error Components" Estimates
1976-1983

Dep. Variable: Net Flow N = 1600

Variable	Parameter Estimate	t ratio
Intercept	12079.4	0.7
M. Atlantic	-527.2	-0.5
Midwest	-117.1	-0.1
Southwest	-679.5	-0.6
Mt. Plains	128.6	0.1
Western	-932.0	-1.0
Southeast	-400.9	-0.3
POP UNDER5	15490.7	2.5**
POP 5-17	-11128.3	-2.9**
POP 18-44	2245.6	2.2**
POP 45-64	8040.1	1.5
POP 65 PLUS	-7757.0	-2.0**
EPR	13292.8	4.3**
ORBA 81	1055.1	0.3
OBRA 82	-991.9	-0.4
PROJECTS	-3.9	-0.4
MAX FSBENR	34.1	1.1
AFDC OPEN	0.7	8.6**
AFDC CLOSE	-0.7	-9.7**
MAX AFDCBENR	-1.3	-0.3
AVG SOCSECR	-82.8	-1.2
AVG SSIR	-7.8	-1.3
BC PEAK	5078.5	1.1
BC TROUGH	-1965.1	-0.4
PEAK LEAD	-2973.0	-1.0
TROUGH LEAD	-1398.0	-0.5
YPCAPR	-353.8	-1.1
URATE	1224.2	4.1**
IURATE/URATE	3831.8	2.0**
URATE(-1)	-991.4	-3.4**
URATE*PEAK	-428.2	-0.9
URATE*TROUGH	551.3	1.5
1977	934.1	0.4
1978	2592.8	1.0
1979	-2479.5	-0.6
1980	-9466.4	-2.2**
1981	-10910.2	-2.5**
1982	-11501.5	-2.0**
1983	-12434.0	-2.1**

**Significant at the .95 level or better.

considerably in some instances. This results in some change with respect to significance tests. The coefficients on maximum real food stamp benefits, all of the business cycle variables, and the 1978 and 1979 fixed effects are no longer significant. It is disappointing to find no support for our hypotheses concerning business cycle effects, including the interactions between the business cycle and the unemployment rate. On the other hand, the OLS results with respect to demographic effects, legislated program effects, and the impact of changing unemployment rates remain relatively unchanged. The estimated impact of EPR is somewhat reduced. The coefficient fell from 14,873 to 13,293, but the error components estimate is within one standard deviation of the OLS estimate, therefore the reduction is not significant. Changes associated with 1981 and 1982 OBRA legislation remain insignificant.

The effects of changes in the unemployment rate and insured unemployment rate remain significant, except for the interaction with the trough of the business cycle, although the effects are reduced in magnitude. The estimated over-all effect of a marginal change in URATE is,

$$\frac{\partial \text{Net Flow}}{\partial \text{URATE}} = 1224 - 428(\text{PEAK}) + 551(\text{TROUGH}) - 3832 \left[\frac{\text{IURATE}}{\text{URATE}^2}\right]$$

At sample means, and ignoring business cycle conditions,

$$\frac{\partial \text{Net Flow}}{\partial \text{URATE}} = 1224 - 3832\left[\frac{3.7}{7.2^2}\right] = 951,$$

which is approximately a 50 percent reduction in the OLS estimate of the marginal effect of a change in unemployment rates. Hence, using OLS we

earlier estimated that the net flow would increase by about 2139 cases given a one percent increase in unemployment rates; the error components adjustment reduces that figure to 951 cases. At the same time the estimated lagged effect is reduced by a little over one-half in the error components model. The coefficients on current and lagged unemployment rates remain fairly close in order of magnitude, although current effects carry slightly more weight.

Finally, the fixed effects associated with time that were estimated to be significant in the OLS model remain significant from 1980 onward in the error components model. The estimated order of magnitude of these effects is reduced marginally.

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VI. Implication for Policy

The purpose of the net flows model is to provide a framework for estimating the effects of policy changes stemming from 1981 and 1982 OBRA legislation upon the change in the food stamp caseload. These estimates should be made controlling for other factors, such as the demographic composition of the population, economic conditions, and changes in other relevant programs, such as AFDC. Over the long-run, the reasons for controlling for demographic effects are clear -- as population increases the magnitude of the net flows will be increased because of the sheer numbers of people moving through the system. Apart from that, the age distribution is of some relevance. Our results suggest that food stamp caseloads tend to increase most given an increase in the number of very young people. In contrast, growth in the elderly population tends to reduce the net flows. One interpretation of this result revolves around the fact that mean incomes of the elderly have been rising in relative terms over the period of our analysis. Mean nominal income of households headed by a person 65 or older rose from $8,708 in 1976 to $15,869 in 1982 -- an 82.2 percent nominal increase or a 7.5 percent real increase. Wages were not rising nearly this rapidly; interest earnings and entitlements income were among the most rapidly growing sources of personal income. Thus, as the population continues to age, in a relative sense, pressures on the food stamp program may be relatively reduced. Of course, this assumes that other elderly-oriented programs, such as SSI and Social Security, remain

as important as they are today, and that other sources of income important to the elderly continue to rise in a strong fashion.

The necessity for economic controls in our analysis is clear as well. A graphical representation of the net flows underscores the potential for confounding business cycle effects with the effects of 1981 and 1982 OBRA changes. Policy changes mandated under 1981 OBRA were implemented, for the most part, in the fourth quarter of 1981 -- one quarter after the official peak of the business cycle. At this time the national net flow was negative, but starting to rise. The policy changes which which were legislated in 1981 did not alter the form of the food stamp program drastically. On balance we might expect them to have a slight negative impact on the change in caseloads. The question then becomes one of how to separate the effects on the caseload of 1981 OBRA changes and business cycle conditions.

Similarly, many of the 1982 OBRA changes were typically implemented in the first quarter of 1983. The official trough of the business cycle was the previous quarter and coincided exactly with the implementation of rounding down of household allotments and deductions, one feature of the 1982 changes. Nationally, food stamp caseloads were rising fairly rapidly at this time, largely due we assume to economic conditions. Again, the question of how to estimate OBRA effects independent of economic effects is raised.

In our analysis we make use of multivariate techniques which take into account a complex set of economic interactions. Our results underscore the importance of unemployment conditions independent of the

business cycle, but we are unable to find a significant effect on the net flow of food stamp cases associated with either 1981 or 1982 OBRA changes. Perhaps this is not surprising since none of the individual changes were so drastic as to expect a big impact on the caseload. In contrast, we did estimate a significant and large positive impact on the net flow of cases associated with the elimination of the purchase requirement -- a policy change that was expected to have a major impact on the food stamp program. This would seem to affirm that the inclusion of policy variables will lead to estimates of significant effects when the impact of the change is strong and unambiguous.

Another clear policy implication to arise from our study is the strength of the relationship between AFDC caseload changes and food stamp caseload changes. It would have been ideal to have estimated food stamp case openings as a function of AFDC case openings, but food stamp data are not available in that form. Our analysis did suggest, however, that AFDC case openings and closings have about equal, although opposite, effects on the net flow of food stamp cases. Hence, policy changes in AFDC are going to have important impacts on the food stamp program.

Finally, in testing for temporal effects in our model we found significant negative fixed effects associated with the years since 1980. Specifically, there has been a tendency toward a net reduction in monthly food stamp caseloads on the order of 11,000 cases or more since 1980. The source of these effects cannot be attributed to demographic or economic conditions, nor to legislated program changes since we have

controlled for these changes. Perhaps we cannot totally discount the notion that the program has been in a sufficient state of flux over the recent years, that our attempts to measure implementation dates of certain measures are far from the mark and the temporal effects we see are really part of the ripple effect of legislated changes. On the other hand, these estimated effects are fairly large -- of a higher magnitude than would be expected from the legislation per se. Another possibility might be that program offices have in general entered a phase in which caseloads are scrutinized more carefully, and there has been downward pressure on program growth.

At present we are unable to provide further clues on the potential sources of caseload changes in recent years. Clearly, additional data for 1984 and 1985 would be helpful along these lines. The addition of more recent data would allow us to estimate the impact of monthly reporting and retrospective budgeting (implemented in early-1984), and to see if the fixed negative effects continue in 1984 and 1985. Also, economic conditions have changed since 1982-1983, and it would be interesting to see if our estimates of economic effects are affected. Presumably, as the economy moves toward an equilibrium, the long-run program effects of recent policy changes can be better estimated through the use of augmented aggregate program data in a net flows modeling structure.

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Appendix A

Variable Definitions

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Table A.1

Variable Definitions

Dependent Variables

SYMBOL	VARIABLE NAME	SOURCE	MEASUREMENT SUMMARY	COMMENTS
NET FLOW	Net change in state Food Stamp monthly caseload.	U.S. Dept. of Agriculture, Food and Nutrition Service. "Food Stamp Program: Statistical Summary of Operations".	Quarterly average of the month to month change in the caseload of individuals. 1970(Q1) to 1984 (Q1).	We subtract the caseload in the previous month from the caseload in the current month to create the net change in persons receiving food stamps. From 1969 through September, 1980 participants were reported separately by "public assistance" and non-public assistance." However, since October, 1980 only total participants are reported and the data are no longer collected according to assistance status.
RAVGBEN	Deflated Monthly Value of issuance per person.	U.S. Department of Agriculture, Food and Nutrition Service. "Food Stamp Program: Statistical Summary of Operations.	Quarterly average of the monthly value of issuance per person. 1970 (Q1) to 1984 (Q1)	Prior to the elimination of the purchase requirement (effective January, 1979) this series contains the bonus value of coupons issued. Starting in January, 1979 the series contains the total value of coupons issued; the "bonus" and total value are identical. The seris is deflated by the Consumer Price Index for food to express the variable in real terms.

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Variable Definitions

Independent Variables

SYMBOL	VARIABLE NAME	SOURCE	MEASUREMENT SUMMARY	COMMENTS
Geographic				
N ENGLAND M ATLANTIC SOUTHEAST MIDWEST SOUTHWEST MT. PLAINS WESTERN	FNS Region	U.S. Department of Agriculture, Food and Nutrition Service. "Food Stamp Program: Statistical Summary of Operations."	Definition used consistently across time. See Table A.2 for listing of states in each region.	Used as dummary variables in analysis. N England is always the omitted category.
N CENTRAL N EAST SOUTH WEST	Census Region	U.S. Census Bureau	Definition used consistently across time. See Table A.2 for listing of states in each region.	Not used in analysis but several other variables are available only by census region.
Demographic				
	State population by Age:	U.S. Census Bureau "P25: Population Estimates and Projections".	Annual 1970-1983, in millions	Quarterly estimates by age are unavailable.
POP UNDER 5	Persons under 5 years of age			
POP 5-17	Persons 5-17 years of age			
POP 18-44	Persons 18-44 years of age			
POP 45-64	Persons 45-64 years of age			
POP 65 PLUS	Persons 65 years or older			
HHSIZE	Average household size	Statistical Abstract of the United States.	1968 to 1983; annual average	This data is not available by state. We include it, however, because benefits per person are a function of family size should be taken into account.

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SYMBOL	VARIABLE NAME	SOURCE	MEASUREMENT SUMMARY	COMMENTS
Food Stamp Program				
PROJECTS	Number of Food Stamp projects.	U.S. Department of Agriculture, Food and Nutrition Service. "Food Stamp Program: Statistical Summary of Operations".	Quarterly average of the number of state projects. 1970 (Q1) to 1984 (Q1)	The number of projects within a state showed great variability in the earlier years of the program. In 1974 in particular the number of projects grew rapidly as the change from commodity distribution to coupon issuance occurred. In recent years the number of projects within a state has been relatively steady. This variable is intended to measure growth in the program and was frozen at its maximum value when used in analysis.
MAXFSBENR	Maximum monthly Food Stamp benefits for four person household; deflated.	Periodic Announcement in the federal register. Summary provided by FNS.	1970-1984	This series does not vary by state. The maximum benefit is defined according to regulations and is periodically adjusted to reflect changes in the cost of the Thrifty Food Plan. (See COLA below.) We deflate the maximum benefit with the CPI for food when used in analysis.
COLA	Cost of Living Adjustment	Periodic Announcement in the federal register.	1970-1984	Dummy variable measuring the indexing of food stamp benefits which occurred annually in July from 1971-1973; semiannually in January and July 1974-1979; reverted to annually in January 1980, and to October in 1982.

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SYMBOL	VARIABLE NAME	SOURCE	MEASUREMENT SUMMARY	COMMENTS
EPR	Elimination of the Purchase requirement	Inferred from the Statistical Summary of Operations	December 1978 to February 1979	Alaska, Florida, Minnesota, New Mexico, Oregon, Rhode Island, Tennessee and Texas implemented in 12/78; the remaining states implemented in 1/79 except in Illinois and New Jersey where it would appear that implementation was more fully completed in February.
OBRA-81	1981 OBRA changes - prorating first month's benefits - gross income standard at 130% of poverty level - reduced earnings disregard	Provided by FNS	October, 1981 to February, 1982	All but six states implemented provisions for new cases in 10/81 or 11/81. Maine, Massachusetts, New York, Utah, Wyoming, and North Dakota implemented by February, 1982. However, many states indicated that total caseload conversion took several months to complete.
OBRA-82	1982 OBRA changes - modified filing unit definition - disabled veterans provision - error rate penalties	Provided by FNS	February, 1983 to May, 1983	About 75% of the states initiated implementation in 2/83 or 3/83; Hawaii, Kansas, Louisiana, Maine Massachusetts, Michigan, Montana, Pennsylvania, Utah, Wisconsin in 4/83; New Hampshire in 5/83; California in 10/83.

SYMBOL	VARIABLE NAME	SOURCE	MEASUREMENT SUMMARY	COMMENTS
Other Programs				
AFDC OPEN	AFDC case openings.	U.S. Dept. of Health and Human Services, SSA, "Applications and Case Discontinuances for AFDC;" and Quarterly Public Assistance Statistics".	Quarterly, 1970 (Q1) through 1983 (Q4).	Variable measures the number of cases opened in a quarter.
AFDC CLOSE	AFDC case closings	U.S. Dept. of Health and Human Services, SSA, "Applications and Case Discontinuances for AFDC;" and Quarterly Public Assistance Statistics".	Quarterly, 1970 (Q1) through 1983 (Q4).	Variable measures the number of cases closed in a quarter.
MAX AFDCBENR	AFDC maximum monthly benefit for a four person family.	U.S. Dept. of Health and Human Services, Office of Family Assistance	1970-1983	AFDC benefits are determined by the state. The series is deflated by the CPI for all items when used in analysis.
AVG SSIR	Average SSI monthly benefit for an aged couple.	House Ways and Means Committee Report "Background Material on Poverty".	1974-1983	SSI benefits are established by the Federal government but states are free to provide supplemental benefits at their own expense. The program was not in effect before 1/74, therefore, this variable used only in analysis of 1976-83.

SYMBOL	VARIABLE NAME	SOURCE	MEASUREMENT SUMMARY	COMMENTS
AVG SOCSECR	Average monthly benefit amount for retired workers, disabled workers, and widows.	Social Security Bulletin, Annual Statistical Supplement	1970-1983	The average social security benefit does not vary by state. The series is deflated by the CPI for all items when used in analysis.
Economic				
BC PEAK BC TROUGH PEAK LEAD TROUGH LEAD	Business cycle peak Business cycle trough Quarter leading the peak Quarter leading the trough	U.S. Dept. of Commerce, BEA, "Survey of Current Business."	1970-83	Peak / Trough 12/69 / 11/70 11/73 / 3/75 1/80 / 7/80 7/81 / 11/82 Measured as a dummy variable equal to 1 in the quarter in which the peak (or trough) occurred, or the quarter leading the peak (or trough).
CPI ALL	Consumer Price Index, all items, urban wage earners and clerical workers.	U.S. Dept. of Labor, BLS "The Consumer Price Index".	Monthly or bimonthly 1968-83; quarterly averages constructed. 1977 (Q4) = 1.0	Available by census region.
CPI FOOD	Consumer Price Index, food at home, urban wage earners and clerical workers.	U.S. Dept. of Labor, BLS "The Consumer Price Index".	Monthly or bimonthly 1968-83; quarterly averages constructed. 1977 (Q4) = 1.0	Available by census region.

SYMBOL	VARIABLE NAME	SOURCE	MEASUREMENT SUMMARY	COMMENTS
YPCAPR	Per Capita Personal Income.	U.S. Department of Commerce. "Survey of Current Business".	Annual 1970-1983. Measured in thousands of dollars.	Available by state on an annual basis in current dollars. Deflated by the CPI for all items when used in analysis
  YDU2 YD2-5 YD5-10 YD10-20 YD20P	% of Families with Real Income: Under $2,000 $ 2,000-$ 5,000 $ 5,000-$10,000 $10,000-$20,000 over $20,000	U.S. Census Bureau "P60: Consumer	Annual 1970-1983.	Available only for the four Census Regions. Income".Annual series expressed in 1983 dollars, percent distribution.
WKEARNR	Average weekly earnings of production workers in manufacturing.	U.S. Department of Labor. "Employment and Earnings, States and Areas".	Monthly 1970-1983; quarterly averages constructed. This series had limited usefulness because of extensive missing data.	Available by state. The series is constructed by multiplying: (1) Avg. hourly earnings of prod. workers in mfg. (2) Avg. weekly hours of prod. workers in mfg. Deflated by the CPI for all items when used in analysis.
URATE	Unemployment rate.	U.S. Department of Labor, BLS "Civilian Labor Force and Unemployment".	Monthly 1970-1983; quarterly averages constructed.	Available by state. Due to sampling considerations, the published data are six-month moving averages for all but the 10 largest states

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SYMBOL	VARIABLE NAME	SOURCE	MEASUREMENT SUMMARY	COMMENTS
IURATE	Insured Unemployment Rate.	U.S. Department of Labor, Unemployment Insurance Service, "Unemployment Insurance Statistics". Publication ceased in March, 1980. Subsequent data are unpublished (by state) and are being provided by the Unemployment Insurance Service.	Monthly 1970-1983; quarterly averages constructed	Available by state.
	% Distribution of Duration of Unemployment	U.S. Dept. of Labor, Bureau of Labor Statistic, "Geographic Profile of Unemployment," and published data	Annual Average, 1976-83. Percent distribution.	Available by Census regions.
DUR5	% Less than 5 weeks			
DUR526	% 5-26 weeks			
DUR2751	% 27-51 weeks			
DUR52	% 52 weeks or longer			

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Table A.2

Regional Definitions

FNS Regions

New England

Connecticut
Maine
Massachusetts
New Hampshire
Rhode Island
Vermont

Mid-Atlantic

Delaware
Washington, D.C
Maryland
New Jersey
New York State
Pennsylvania
Virginia
West Virginia
Puerto Rico
Virgin Islands

Southeast

Alabama
Florida
Georgia
Kentucky
Mississippi
North Carolina
South Carolina
Tennessee

Midwest

Illinois
Indiana
Michigan
Minnesota
Ohio
Wisconsin

Southwest

Arkansas
Louisiana
New Mexico
Oklahoma
Texas

Mountain Plains

Colorado
Iowa
Kansas
Missouri
Montana
Nebraska
North Dakota
South Dakota
Utah
Wyoming

Western

Alaska
Arizona
California
Hawaii
Idaho
Nevada
Oregon
Washington
Guam

Census Regions

Northeast

Maine
New Hampshire
Vermont
Massachusetts
Rhode Island
Connecticut
New York
New Jersey
Pennsylvania

North Central

Ohio
Indiana
Illinois
Michigan
Wisconsin
Minnesota
Iowa
Missouri
North Dakota
South Dakota
Nebraska
Kansas

South

Delaware
Maryland
District of Columbia
Virginia
West Virginia
North Carolina
South Carolina
Georgia
Florida
Kentucky
Tennessee
Alabama
Mississippi
Arkansas
Louisiana
Oklahoma
Texas

West

Montana
Idaho
Wyoming
Colorado
New Mexico
Arizona
Utah
Nevada
Washington
Oregon
California
Alaska
Hawaii

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Appendix B

Descriptive Statistics

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Table B.1

I. Descriptive Statistics -- Continuous Variables
1970-1983

Variable	N	Mean	Standard Deviation	Minimum	Maximum
POPU5 (000,000'S)	2652	.322	.333	.028	2.008
POP5-17 (000,000's)	2652	.958	.986	.088	4.996
POP18-44 (000,000's)	2652	1.670	1.808	.115	11.299
POP45-64 (000,000's)	2652	.856	.932	.041	4.710
POP65P (000,000's)	2652	.464	.498	.007	2.615
HHSIZE	2652	2.88	.14	2.72	3.14
PROJECTS	2554	57.1	44.4	1.0	254.0
MAXFS	2652	183.2	55.6	106.0	401.0
MAXFSR	2618	176.48	12.66	149.68	258.96
NET FLOW	2596	1983	10665	-82811	131354
AVGBEN	2598	27.73	11.78	5.31	238.96
AVGBEN R	2511	26.04	5.67	-	-
AFDC OPEN	2588	8476	12264	15	93320
AFDC CLOSE	2584	7951	12526	140	117479
MAX AFDC	2652	295.36	115.92	60.00	751.00
MAXAFDC R	2652	290.99	106.25	60.00	596.64
AVGSSI	2040	128.14	49.71	-	564.83
AVGSSI R	2040	109.73	38.64	-	590.85
AVGSOCSEC	2652	261.65	94.34	123.82	410.23
AVGSOCSEC R	2652	243.30	18.76	191.38	275.17
CPIALL	2652	1.06	.33	.61	1.64
CPIFOOD	2618	1.04	.31	.58	1.55
YPCAP (000's)	2652	7.246	2.716	2.556	16.598
YPCAP R (000's)	2652	6.787	1.085	4.064	12.119
IURATE	2650	3.82	1.89	0.50	14.83
URATE	2646	6.67	2.39	1.67	20.50
URATE (-1)	2595	6.65	2.39	1.67	20.50
UR*PEAK	2646	0.35	1.48	0.0	11.23
UR*TROUGH	2646	0.59	2.16	0.0	16.20
DUR UNDER 5	1604	42.9	7.7	21.0	65.6
DUR5-26	1604	44.5	4.0	32.5	57.7
DUR27-51	1604	6.7	3.1	0.0	17.9
DUR52P	1604	5.8	3.8	0.0	23.1
YD UNDER 2	2652	1.7	0.5	0.8	2.9
YD2-5	2652	2.8	1.0	1.2	4.7
YD5-10	2652	9.5	1.5	7.1	12.2
YD10-20	2652	23.6	2.3	20.1	30.1
YD20P	2652	62.5	4.7	52.1	69.9

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Table B.2

II. Descriptive Statistics -- Discrete Variables
1970-1983

Variable	N	Mean	Sum
N. England	2652	.14	364
M. Atlantic	2652	.14	364
Midwest	2652	.12	312
Southwest	2652	.10	260
Mt. Plains	2652	.20	520
Western	2652	.16	416
Southeast	2652	.16	416
EPR	2652	.39	1028
OBRA 81	2652	.17	458
OBRA 82	2652	.07	190
BC PEAK	2652	.06	153
BC TROUGH	2652	.08	204
PEAK LEAD	2652	.06	153
TROUGH LEAD	2652	.06	153

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Table B.3

I. Descriptive Statistics -- Continuous Variables
1976-1983

Variable	Mean	Standard Deviation	Minimum	Maximum
POP05 (000,000's)	.324	.331	.032	2.008
POP5-17 (000,000's)	.942	.950	.093	4.809
POP18-44 (000,000's)	1.805	1.916	.149	11.299
POP45-64 (000,000's)	.882	.941	.076	4.710
POP65P (000,000's)	.503	.526	.034	2.615
HHSIZE	2.78	.06	2.72	2.89
PROJECTS	61.5	46.6	1.0	254.0
MAXFS	216.44	36.91	166.00	401.00
MAXFS R	176.07	8.95	163.12	258.54
NET FLOW	831	9545	-82811	101810
AVG BEN	33.35	9.79	16.80	238.96
AVG BENR	27.23	5.68	-	-
AFDC OPEN	9138	12359	15	86541
AFDC CLOSE	9180	13492	316	117479
MAX AFDC	327.16	114.84	60.00	625.00
MAX AFDCR	266.30	97.45	60.00	580.79
AVG SSI	136.77	50.12	34.48	564.83
AVG SSIR	109.11	39.91	24.96	590.83
AVGSOCSEC	321.83	67.13	218.40	410.23
AVGSPCSEC R	255.02	7.44	235.60	275.17
CPIALL	1.26	.25	.89	1.64
CPIFOOD	1.23	.21	.89	1.55
YPCAP (000'S)	8.727	2.142	4.443	16.409
YPCAPR (000's)	6.927	0.969	4.762	10.320
IURATE	3.69	1.55	.50	10.90
URATE	7.17	2.37	2.23	20.50
URATE(-1)	7.16	2.37	2.23	20.50
UR*PEAK	.42	1.67	0.0	11.23
UR*TROUGH	.52	2.11	0.0	16.20

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Table B.4

II. Descriptive Statistics -- Discrete Variables
1976-1983
N = 1600

Variable	Mean	Sum
N. England	.14	224
M. Atlantic	.14	224
Midwest	.12	192
Southwest	.10	160
Mt. Plains	.20	320
Western	.14	224
Southeast	.16	256
EPR	.63	1007
OBRA 81	.28	449
OBRA 82	.17	186
BC PEAK	.06	100
BC TROUGH	.06	100
Peak LEAD	.06	100
Trough LEAD	.06	100